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Landscape Architecture and Big Data: *It's crunch time*

A dissertation submitted in partial
fulfillment of the requirements for
the Degree of Master of Landscape
Architecture at Lincoln University 2016

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1.0 Introduction

This dissertation began with a book.

While flicking through a range of design-related books at a local bookshop, one left me amazed and left a lasting impact. The book, *London: The Information Capital* (Cheshire & Uberti, 2014), contained an array of large datasets and information that were displayed in ways I had never contemplated before. As I stopped skimming and read the introduction more thoroughly, it discussed how each day we are all increasingly producing an immense amount of data, or big data, and that New Zealand is ranked fourth in the world by the amount of data it makes publically available through governmental agencies (see Figure 1). This was something that captivated me, especially

when we were significantly ahead compared to other developed countries such as Australia or Norway.

I work with data in a number of ways in my teaching role and see that many of the projects that students within the Landscape Architecture programme here work on, require collecting and analysing site data. Cheshire and Uberti's book made me stop and question how much big data I was using and if it were beneficial to myself or students when dealing with a real site. So the questions I began to ask were whether landscape architects take advantage of big data and what tools are available to analyse them.

Country Explorer

The explorer allows you to analyse the results for individual countries. Select a country from the map below to view key figures.

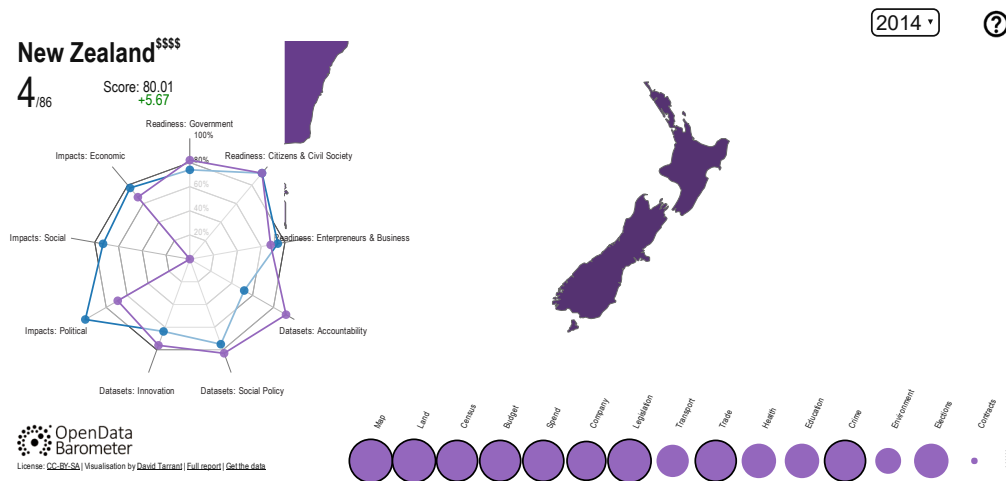


FIGURE 1: Open Data Barometer: 2014 Global Report showing New Zealand's ranking of 4th in the world for its open data rating. Image: Web Foundation (2015)

1.1 What is "big data"

The term 'big data' has been used since the early 2000s as the personal computer has gained in popularity, but the term was first used academically by Diebold (2000) to assist with statistical forecasting. Diebold later points out that he was not exclusive in using the term and that it was first used by industry in the mid-1990s by Silicon Graphics and showed a "clear awareness of Big Data the phenomenon" (Diebold, 2012:3).

Finding a definition of big data would seem a simple task but one soon discovers that a definitive scope of big data is wide-ranging. Mayer-Schönberger and Cukier state that "there is no rigorous definition of big data" (2013:6) and that it is not necessarily big "in absolute terms" (2013:28) as our perception of what is 'big' will no doubt change with time and

technological advancement. The notion of 'big' can also refer to not just one large dataset but also many datasets accumulating into a larger set. After carrying out a survey of the different definitions that have been previously presented, De Mauro, Greco and Grimaldi (2015) proposed that the definition include three V's to describe it: Volume, Velocity and Variety as shown in Figure 2.



FIGURE 2: The three V's of big data. Image: James (2013)

It is important to introduce the similar, but not identical, concept of “Open Data” which can be defined as:

“Open data and content can be freely used, modified, and shared by anyone for any purpose” (The Open Definition, n.d.).

1.2 Big data's increase and availability

Through web-based portals and live streams, fed by a growing, connected and mobile culture, data is growing at an exponential rate. Estimations of the volume of stored data in the digital world will increase from 300 exabytes

(1000⁶) in 2007 (Mayer-Schönberger & Cukier, 2013) to over 40 zettabytes (1000⁷) in 2020 (Havens, 2014). This data is not only growing in volume, but is also becoming increasingly diverse (Soubra, 2012) as shown in Figure 3, and more available to not just businesses but to the wider public through the rise of open data policies in place by governments (Gurin, 2014).

The main difference between open data and big data is that open data is fundamentally accessible to the public, whereas big data is not necessarily public nor easily accessible (see Figure 4). Both can be large volumes of data,

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FIGURE 3: Big data is increasing in all directions. Image: Soubra (2012).

therefore open data can be big data; big data can also be accessible and therefore could be referred to as open data. For the purposes of simplicity in this dissertation, I will use the term big data to describe a large number of datasets which contain user or geographic information that is accessible.

In New Zealand, the government has placed particular emphasis on making large datasets available to the public. In 2008 the government launched the 'Open Government Information and Data Work Programme' (also referred to as the Open Data programme) and continued this priority with the 'Declaration on Open and Transparent Government' in 2011. Internationally, the United Nations has created

the Global Pulse initiative which aims to harness big data for development and humanitarian action, and a Data Revolution Group. There are independent initiatives such as the International Open Data Charter 2015 which mandates that signatories follow its principles and best practices for releasing open governmental data to ensure it is accessible, usable and comprehensive.

Another aspect of big data's increase is revealed in the breadth of its application throughout many areas of society, science and research. TED, a prominent and global innovation-driven community of scientists, thinkers and designers, has 137 results for talks and presenters which discuss big data. These

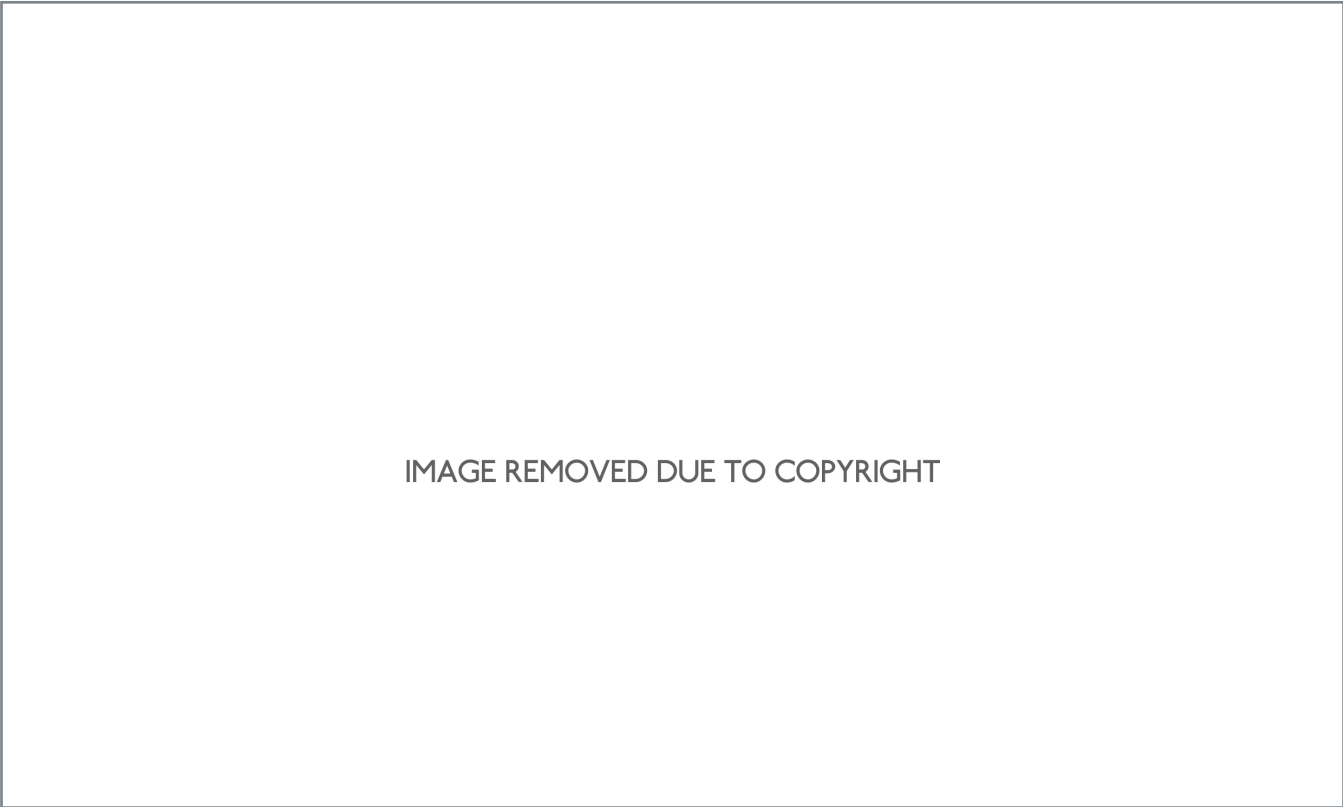


FIGURE 4: Venn diagram showing relationships between big data, open data and open government according to Gurin. Image: Gurin (2014).

range from using big data to inform healthcare providers and law enforcement, to addressing global issues such as climate change, or finding the best place to park in a city.

1.3 The significance of big data

The increasing volume and availability of big data has led to an increase in its significance. As mentioned, big data has spread into many fields and this has had a major influence. Although critics have touted it as just hype, there are several characteristics of big data that have made an impact and show how it has become significant.

A key attribute of big data that has helped increase its significance is its ability to capture all (or at least a large percentage) of a dataset. Previously this was not possible due to factors such as cost. Datasets relied on samples from which to derive correlations (Mayer-Schönberger & Cukier, 2013). This reduced reliance on forms of information gathering, such as sampling, has provided for a better representation within the datasets, and all of this has been made possible as our ability to process large quantities of data has increased. These datasets are more inclusive of an entire layer, a population, a scenario, a narrative.

Using big data to build our understanding and to make predictions is another attribute which has added to its significance. Mayer-

Schönberger and Cukier note that it helps us to see relationships between disparate pieces of information and “points us toward understanding” (2013:197). This understanding of relationships and correlations can be used to inform decisions based on verifiable data, and this data is becoming more central to decision-making and sustainable development (Barroso & Le Goulven, 2014).

1.4 Big data in design

Landscape architecture is a complex, interdisciplinary profession which takes into account many different streams of information and uses a broad scientific knowledge whilst applying an artistic creativity at the same time (Gazvoda, 2002). Landscape architects already use a wide range of tools for design (Gonot, 2013) and it is appropriate that we should make use of available big data. Big data is beginning to be explored within landscape architecture with individual social media datasets, such as Flickr with their geotagged photos, revealing how people interact with the environment (Lee, 2013).

Though the topic of data analysis is not new to landscape architecture (Steinitz, 1990), the continuing increase in data volume, variety and availability and how it can be incorporated into landscape architecture, is not widely discussed. Prominent landscape architecture theories, such as Landscape Urbanism, have underlying

principles that benefit from (nay demand) the use of big data (Weller, 2007).

Landscape architecture is often exploring ways of interpreting and representing attributes of the landscape which are unseen. Amoroso discusses how landscape can be represented using data originated from the site, and how “they can visualize the intangible and often invisible forces that shape our environment” (2015:4).

With the increase of data-reliant systems such as parametric modelling and Building Information Modelling (BIM) within the design of buildings and large infrastructure projects, big data is the single most important ingredient for creating ‘Smart Cities’ (Townsend, 2013).

Woods Bagot, a global design and consulting firm, has developed a design process named ‘Super Space’ which works with unlocking big data to create human-centred experiences.

Within the urban design realm, big data has so far been mostly used by city government for operational purposes: to save money and improve services. However, it has been used rather less for planning and design to date.

Research into big data has concentrated on other industries such as health, retail and transport. What we see from those industries is that big data has great potential to improve design through analytics (Royal Institute of British Architects & Botazzi, 2014).

Design professionals in related fields are using big data to innovate and provide successful outcomes, and there is the opportunity for big data to inform landscape architects in making design decisions.

With the increase in public scrutiny in civic spending through the media and community groups, as well as the constant need to design fiscally responsible and sustainable projects, evidence can be provided through the inclusion of big data in our design processes. To include big data effectively, the appropriate data analysis tools need to be available.

1.5 Research Questions

This research will focus on placing big data analysis into the existing body of landscape theory, identifying the potential for working with big data in landscape architecture, as well as identifying significant gaps in its application.

Figure 5 (overleaf) shows my diagramming of areas of interest, and in particular, my research questions are:

1. What data analysis approaches do landscape architects currently use?
2. Does landscape architecture have the necessary tools to inform design outcomes using big data?

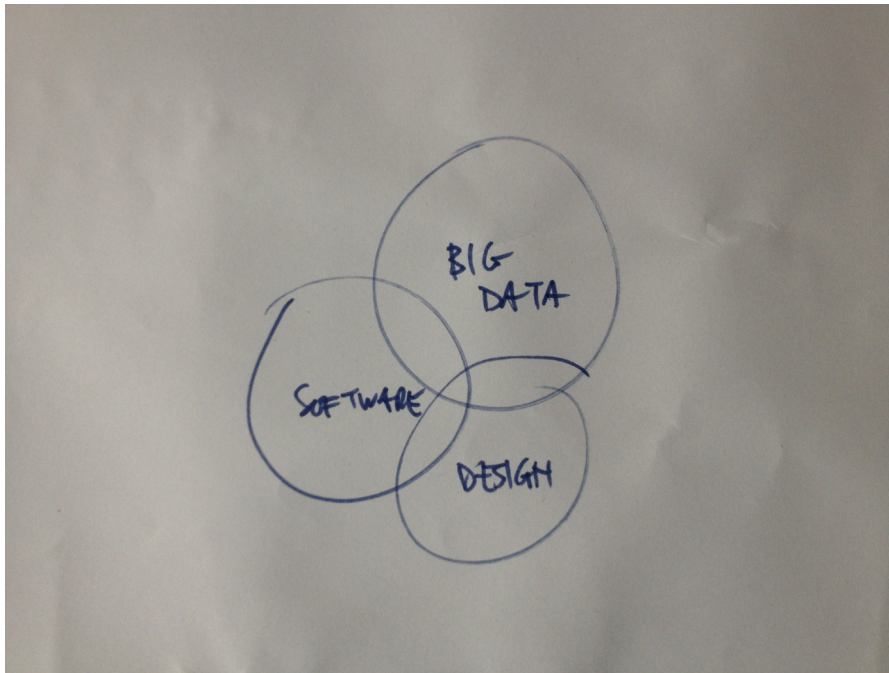


FIGURE 5: Initial mapping for the research questions

3. What obstacles are there when working with big data?
4. What gaps need to be addressed to ensure landscape architects can use big data to inform their decision-making in site design?

My overwhelming concern was how landscape architecture is, or can be, connected to big data. Figure 6 expresses their relationship as one which relies on both machine processing and cognitive processing.

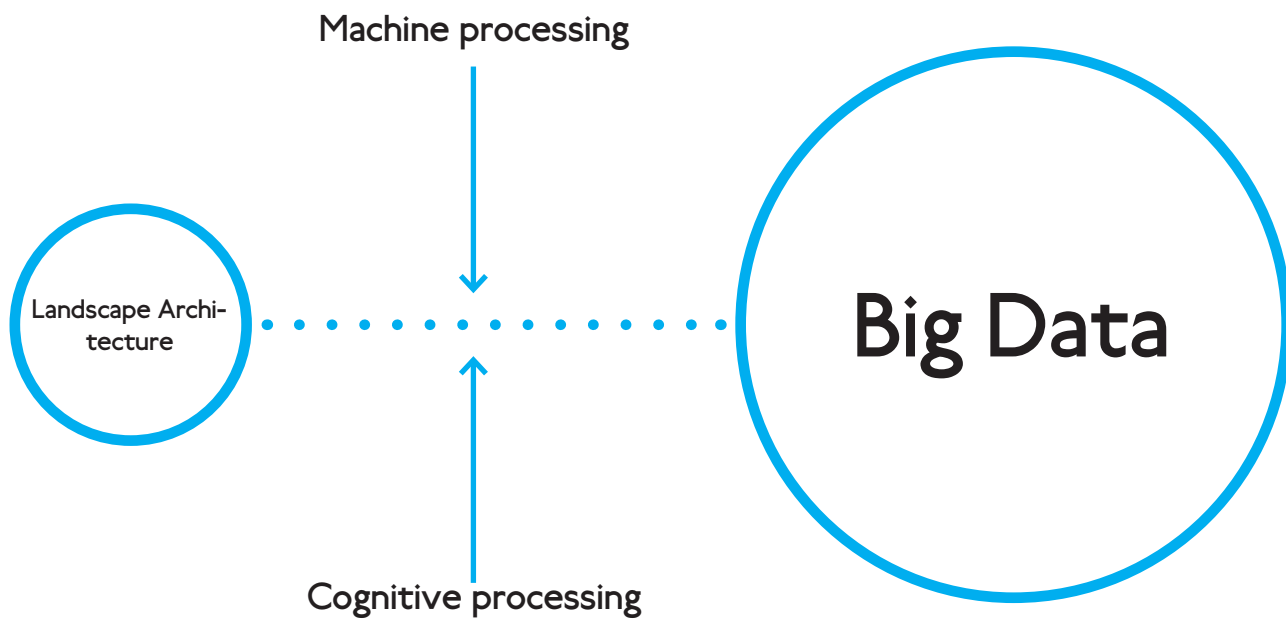


FIGURE 6: Identifying connections to connect landscape architecture with big data

2.0 Methods

2.1 Scoping

My research has been exploratory in character, with the initial question of “do landscape architects use big data” forming the direction in which it has been guided. Defining what big data actually was shaped the early phases as there was no indicators as to what I was looking for and where I would find it.

2.2 Literature Review

Using a preliminary set of keywords, my research located a broad setting of readings and these framed the background to comprehending the sphere of knowledge in this field and how diverse the terminology

was (which required constant rationalisation). Once this was complete, a literature review was undertaken, revealing the current data analysis approaches from within the profession of landscape architecture along with those from other fields. The literature review also sought to identify common themes between them, as well as any potential gaps that could be investigated. This research method was a key part of the process as it not only outlined the current known body of knowledge, it revealed which avenues required further investigation and helped crystallise the research questions as a result.

2.3 Data Collection

A parallel line of inquiry, as shown in Figure 7, was the collection of data. A site was selected on the following criteria: a significant civic space (such as a park), one that has a high-profile within the landscape architecture profession (such as a sustainable design exemplar) and the potential for collecting a large amount of data. Waitangi Park in Wellington, New Zealand, was decided upon. The collection of the data then began in an ad-hoc manner as the data was found spread out across multiple sources such as government agencies and social media, but began to be more directed once I had explored precedents of big data categories and adapted these into a proposed set of categories. This provided me with a clearer approach as the data sources were more accurately targeted and revealed which categories of big data were missing or unobtainable.

2.4 Critique

The second phase involved a qualitative methodology using a descriptive critique and a criteria matrix by which the identified data analysis approaches were evaluated. The critique outlined each approach's process and workings as well as looked at how they addressed big data. The criteria matrix was more evaluative and gave a score for seven different criteria; three of these related to the

attributes of big data, and four related to their feasibility for practicing landscape architects.

Three data analysis approaches were selected based on highest scores with two from the known body of landscape architectural practice and one from outside of this.

2.5 Case Study

The method for testing these was decided to be done through a case study site – Waitangi Park. The case study method was chosen as it provided a grounded method that enabled the application of the data analysis approaches in a more exploratory way than merely discussing the possibilities. It also demonstrated a process that landscape architects could follow and make use of.

2.6 Data Analysis

The final phase involved the three data analysis approaches being applied to the case study site using the datasets gathered as described in the literature, and then summarised for discussion to identify benefits, weaknesses and gaps that needed to be addressed.

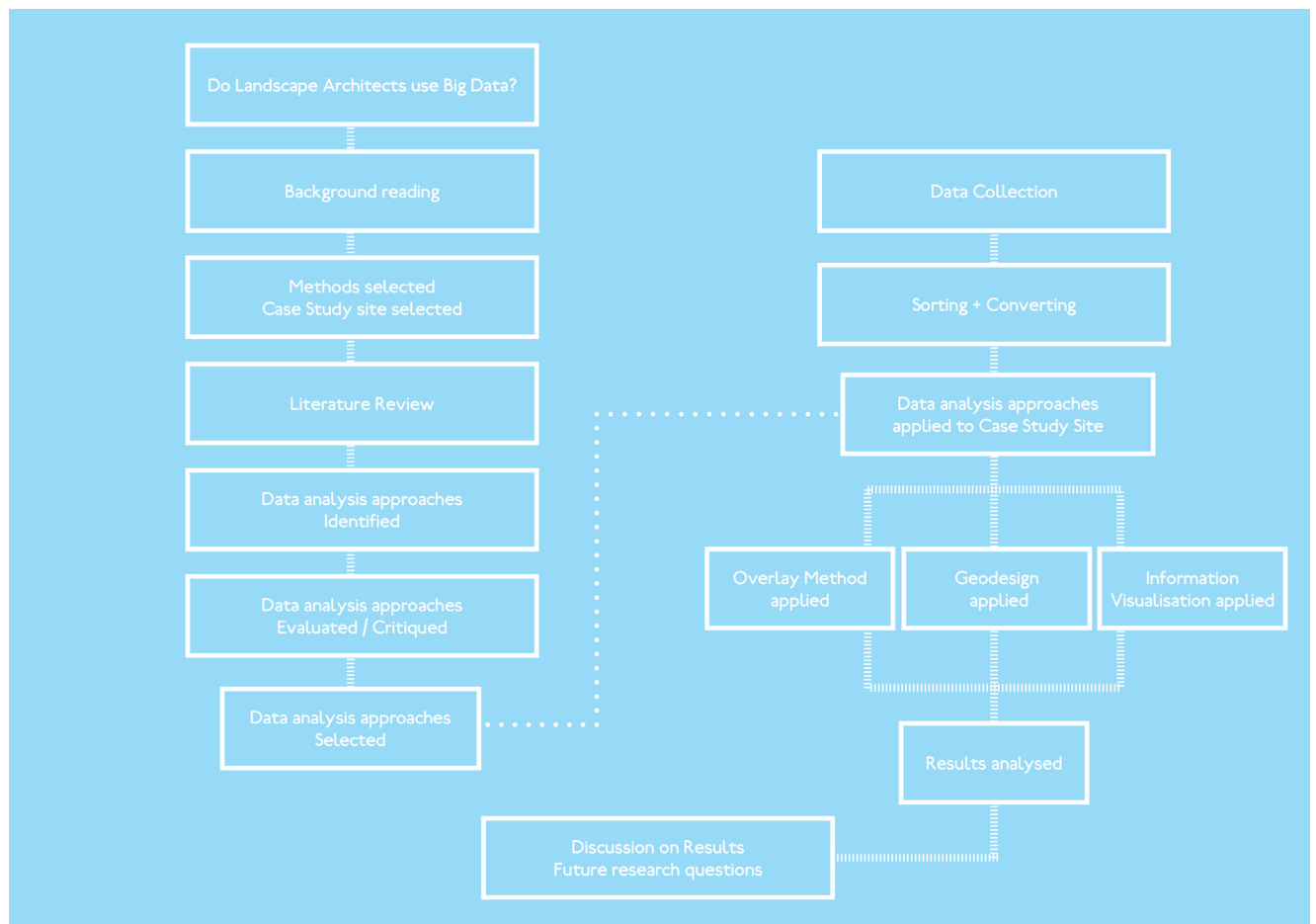


FIGURE 7: Flowchart of the parallel research process followed. The converging of the data stream and literature stream is shown as a dotted line

3.0 Data analysis approaches

3.1 Literature Review

This literature review has been divided into the four broad themes which recur throughout the literature when addressing data analysis: understanding the data; communicating the information effectively; the relevance of context; and the end goal of data analysis - outcomes.

As I began this literature review, it quickly became apparent that there were limited papers and publications that covered both the topics of landscape architecture and big data, and that where there were some published works they were very recent (within the last three years). When I collated the number of publications found in Google Scholar that had

the phrases “landscape architecture”, “big data” or both, the results were alarming. As can be seen in Figure 8, the number of published works discussing landscape architecture have been declining since 2012, at which point published works on big data begin to soar and climb steeply above landscape architecture. Published works on both phrases were increasing – but were still negligible. When the same process was applied to Google Trends (which is based on how often a particular search-term is entered relative to the total search-volume in Google Search) there was some hope as, even though the phrase “landscape architecture” was still in decline, the inclusion of both phrases paralleled the increased search frequency of big data.

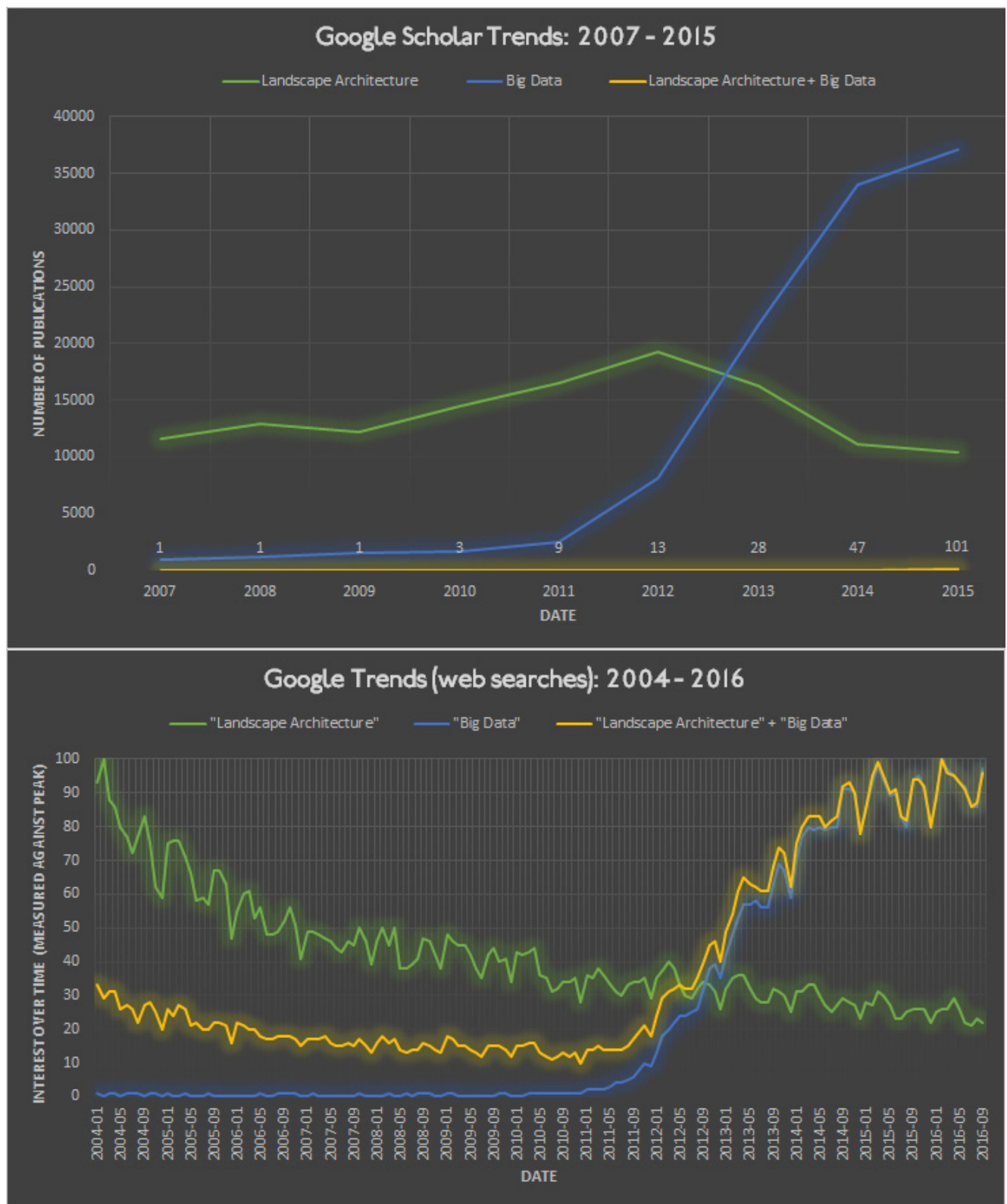


FIGURE 8: Frequency graph of phrases for landscape architecture and big data in Google Scholar and Google Trends. Landscape architecture frequency is shown as a green line, big data as blue, and the inclusion of both in yellow

3.1.1 Interpreting

Interpreting data is at the core of data analysis (Boyd & Crawford, 2012), and within the literature interpretation is achieved through methods such as working with layers of information, by asking questions or by exploration through graphic media.

The use of layers is a recurring theme in landscape architecture approaches and can take the form of analogue tracing sheets or complex digital datasets. The first form was made popular by the book *Design with Nature* (McHarg, 1969) where he took discrete datasets, placed them into single layers of information, then overlaid them onto a site to 'reveal' a deeper understanding of the information. The major difference between how McHarg used overlays and how others before used them, such as Elliott (Motloch, 2000) was that he included layers which hadn't been incorporated before, such as 'ecological values'.

Another method of using layers to understand data in the literature is through computer programs, specifically Geographic Information Systems (GIS). Whilst the program in itself doesn't automatically understand the data, the way in which the data is combined and processed is where understanding is achieved. Design processes such as Geodesign have attempted to incorporate layers of knowledge

within a framework from a variety of sources but even McHarg acknowledges that this method has not advanced much further than his approach 30 years earlier (Dangermond, 2010). Using layers of information is suitable when they are formatted correctly and rely on geocoded data but complex layers, such as integrating social and ecological values, have rarely been attempted using GIS (Ryan, 2011).

One concept identified in the literature discusses how data can be understood by asking the right questions. Etlinger (2011) identifies that current analytics require writing a 'query' or a question to understand the data, and Steinitz (1990) extends this concept of querying by using a set of six questions as part of the analysis:

1. How should the landscape be described?
2. How does the landscape operate?
3. Is the current landscape working well?
4. How might the landscape be altered?
5. What predictable differences might the changes cause? And
6. How should the landscape be changed?

Graphic media, especially the production of hybrid diagrams such as 'datascares', can also demonstrate ways for interpreting complex relationships (Hansen, 2015). Visual representations can include both maps and

diagrams as they merge more than one display method and can take into account the “plethora of data” (Hansen, 2015:29) available to us to inform site design. After all, understanding is the main goal since data only identifies the problem (Shen & Long, 2015).

3.1.2 Communicating

Communicating the data through visual representation is a common component of the data analysis approaches identified within the literature. Major themes become apparent such as the efficiency of visual perception through

cognitive processes to absorb large amounts of data, that design is required for the greatest benefit, and that designers use this form of communication for not just themselves but for informing the networks that they are involved with.

Our cognitive systems can process information to identify properties, regularities, patterns or relationships, and using visual representations in the analysis of data is one of the approaches that benefits from this human skill (Mazza, 2009). These data visualisations can be very effective if designed well, turning unappealing and bland

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FIGURE 9: Beck’s 1931 London Underground map. Image: Beck (1931)

datasets into engaging and powerful agents of change – or as Lankow, Ritchie & Crooks put it, “Design is to data what cheese sauce is to broccoli” (2012:40). The con of these visual representations is that if the selected method of displaying the data is not well chosen, it can be misleading or worse – wrong (Tufte, 1997).

Cognitive systems can also process information subconsciously as Novich and Eagleman (2015) showed through the use of encoded vibro-tactile information being processed by the brain through contact with skin. Communicating information in ways that are not reliant on visualisations are being explored and is an area of development.

An example of a simple yet complex demonstration of an information visualisation is Henry Beck’s 1931 map of the London Underground. Shown in Figure 9, Beck chose to alter the accuracy of London’s geography in order to create a better system of display, and his ‘map’ has been held up as an exemplary visualisation (Cheshire & Uberti, 2014).

The interface for communication is also changing with advances in technology and online platforms using Flash, HTML5 and other coding languages. Periscopic, who is a socially-conscious data visualisation firm, uses these to inform their data analysis approach - Data Storytelling - to create interactive visuals to

enable users to see the data in multiple ways including splitting the data or watching patterns unfold over a time period.

The final theme relating to the communication of information is that as designers, we work within a democracy and as such, we inform the public through these data analysis approaches and are required to communicate with clarity and transparency (Steinitz, 2010). Landscape Architecture is a “social phenomenon” (Swaffield, 2002:183) that is working in relationships between individuals, groups and wider socioeconomic processes and therefore should aim to provide this data in ways that are efficient, engaging, stimulating and informing.

3.1.3 Context

While predictions can be easily made, the power of big data is in its context (Lohr, 2015) and using the appropriate analysis approach is vital to ensuring the veracity of the decisions that come out of the data. Context provides meaning to the data for the user as it enables it to be seen within the networks of what we already know and understand (McCandless, 2014). “[T]aken out of context, data lose[s] meaning and value” (Boyd & Crawford, 2012:670) and if we are to work with these diverse datasets we need to consider the context in which it was collected.

3.1.4 Outcomes

The end goal of the data analysis approaches is to reach some form of an outcome, including making predictions about the future to inform decision-making. Mazza emphasises that this is an important trajectory and that we need “effective methods that allow us to go through this information” (2009:1). While Mazza and others see predictions as achievable, some such as Hill (2005), state that trends cannot be predicted when we integrate nature and culture and that surprises should be expected. Whether prediction is achievable or is a flawed concept, one thing appears clear – that the technologies we currently use to evaluate current and potential future conditions, are changing at accelerating paces (Steinitz, 2010).

Exploring possible design solutions and evaluating these alternative futures is another outcome from analysing big data. Geodesign is an approach which follows this idea by creating simulations which are “informed by geographic contexts” (Flaxman, 2010).

3.2 Data analysis approaches: critique + matrix evaluation

From the literature review, a number of data analysis approaches were identified in the literature and there was a clear distinction between those which were found to be part

of the theory of landscape architecture, and those outside of it. In Figure 10 I locate these approaches on a matrix, highlighting an emphasis on those which have the ability to process more data, and those that rely on more cognitive ways of processing.

The prominent data analysis approaches shown to be used in landscape architecture theory for dealing with site data are the SAD (Survey-Analysis-Design) method, the Overlay Method (often referred to as Ecological Design) and Geodesign (Turner, 2014). Of note is the prevalence of the use of ‘layers’ in each of the three approaches.

Data analysis approaches outside of this body of knowledge identified for critique and evaluation are Data Visualisation (Tufte and McCandless), Data Storytelling (Periscopic), Data Augmented Design (Shen and Long), and Data Sensory Perception (Novich and Eagleman). These could prove useful in pushing or dissolving the boundaries between analysis methods in different fields and could assist designers to work with big data in new and meaningful ways.

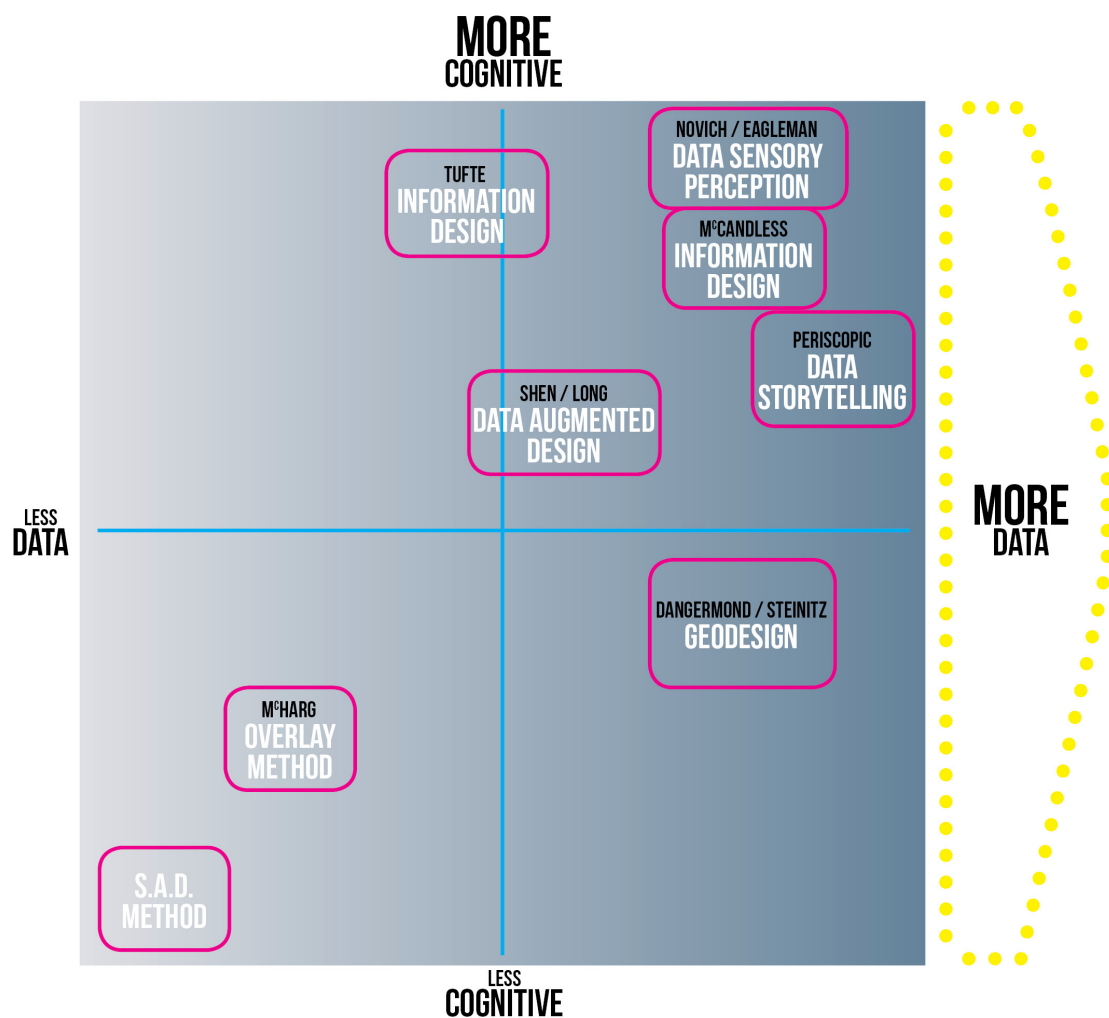


FIGURE 10: Locating data analysis approaches (as identified in the literature review) within a quadrant matrix

3.2.1 Critique of current data analysis approaches

The next phase in this literature review is to carry out a descriptive critique of all the aforementioned approaches, then evaluate them based on a criteria matrix using seven criteria to evaluate each approach. The first three address the three V's of big data (Volume, Variety, and Velocity), with the remaining four criteria evaluating their application for practicing landscape architects (cost implication, ease of use, geospatial context, and ability to work at a range of scales).

SAD method

The SAD method is a three step process of design which is based on the premise that "design 'problems' should be 'solved'" (Turner, 2014) and often involves three sheets of paper. The steps are Survey, Analysis, and Design with minimal 'layers' of information and therefore limited scope for large datasets. It is a quick and minimal approach to data analysis in a site context.

Overlay Method

The Overlay Method was first used by Charles Elliott (Motloch, 2000) with McHarg taking it further using suitability analysis as its dominant outcome and this further application of the technique has possibly encouraged its use within landscape architecture (along with the

popularity of the term 'ecological design').

The degree of its integration with big data is limited due to the limited number of layers of discrete data that can be included at any one point and instead summaries or further steps in the process are required to make sense of the results. It does however have the ability to work with a variety of scales but certainly is more applicable at a larger scale such as at a regional level (Turner, 2014). The technique itself contains no mechanism to process data but does allow the ability to give the information a hierarchy - which could later be used in analysis. This lack of a mechanism also means that there is a simple linear process that is followed and McHarg himself acknowledged this with his statement: "... where any man, assembling the same evidence, would come to the same conclusion" (Turner, 1996:146). Finally, there is no capacity to work with non-spatial inputs as the layers require surveyed, geolocated data.

Geodesign

This approach has its roots in the Overlay Method (Turner, 2014) and has been influenced by Steinitz's model of landscape change which addresses landscape futures by asking geographic questions. There is still a strong focus on suitability maps (as found in the Overlay Method) and these are produced alongside charts, graphs and statistics (Dangermond, 2010).

Miller notes the advantages of the geodesign approach as being able to handle complex sets of geospatial data but that the digital tools used "... are non-intuitive and relatively difficult to use" (2012:22). The geospatial analysis tools, such as Geoprocessing Tools, require a predetermined set of land uses or land-use management strategies in order to assess or create an output (Miller, 2012). These outputs are either geographic displays such as maps, or scalar values (working with a shape).

DAD (Data Augmented Design)

The Data Augmented Design approach was developed by Shen and Long and seeks to "quantitatively understand" urban orders within this new data environment using big data (Shen & Long, 2015:12). It involves the specific selection of datasets to include surveyed data, sensed data, and urban ordering data, with the use of an advanced spatial information system to analyse and model the raw data. Outputs can be displayed as a series of visualised results – whether these would be shown as geospatial maps or graphics are not clear.

The major advantage of this approach, as stated by Shen and Long (2015), is that it is a framework that is scientific and removes any knowledge or innovation inadequacies a designer may have.

Data Visualisation

This is the broadest of all the approaches critiqued and there are numerous individuals who have furthered this such as Tukey (1962), Tufte et al (1980), McCandless (2009) and Yau (2011). Due to this spread of thinking within the overall approach, I have identified two splits: Tufte with an approach that is reliant on simplifying data, and McCandless who seeks to use technology as well as cognitive processing to analyse data. These two divergent approaches have appeared due to the dominance of academics and scientists in the area of information design now being shared with Internet users who also appreciate their effectiveness (Lankow, Ritchie & Crooks, 2012).

Both approaches are governed by rules or guiding principles of 'good design' with the Tufte approach more so, and both are explorative rather than narrative (although the McCandless approach has an element of narrative mixing).

The level of content that can be processed relies on the tools used for each and as previously mentioned, the McCandless approach uses technology such as Google Sheets and online platforms such as HTML5 to display the outputs and can therefore process a larger number of large datasets. There is still a significant reliance on the 'designer' to look at the data and question it, investigating which

visual methods would aid its processing, giving a more qualitative than quantitative output.

Data Storytelling

Data Storytelling is an approach that has been used as a method to use technology (predominately coding) to tell a story using datasets. Periscopic is an example of how this has been applied and the impacts it could have are identified through their statement: "...our goal [is] to use technology to visualize solutions that engage the public and deliver messages of action." (Citraro, 2010).

This approach is time consuming, bespoke to each and every story that the data is used for, and requires specific coding skills (HTML5, JavaScript, Flash etc.). Periscopic considers that the creators of this approach are "data visualizers, scientists, flâneur, and sloggers" and come across insights and relationships that were previously unseen (Citraro, 2014).

Many of the visualisations used as a narrative device are interactive; stories that can be split, interrogated and layered. The interactive visuals are also more about ensuring the user is engaged with the data rather than "dumbing down the data" Periscopic (2013).

Data Sensory Perception

The precept for this approach is that we have developed our senses as our brains have

become familiar and learned to recognise the information it receives. Novich and Eagleman (2015) encoded vibrotactile information (using motors embedded in a vest) and through a series of experiments showed that the skin can convert the encoded information in a way that the brain can recognise and process. Although highly experimental, this approach is adaptable to suit specific datasets and this was demonstrated during Eagleman's TED2015 talk in Vancouver in March 2015 where he wore the vest and was 'sensing' twitter handles that related to the conference live during his talk. This approach is the most technologically advanced of the approaches critiqued and shows the highest level of connection between user and the data.

3.2.2 Matrix evaluation

For the matrix evaluation, shown in Figure 11, each approach was given a score under each of the seven criteria according to the following grading:

xx	= -2	: Did not address criterion at all
x	= -1	: Did not address criterion well
√	= +1	: Addressed criterion somewhat
√√	= +2	: Addressed criterion well

The seven criteria used relate to their incorporation of big data and applicability within a professional design office. The big data criteria relate to the three V's (refer to Figure

2), while the professional application criteria addresses the cost to carry out the approach, the usability of the approach and level of skill required, whether the approach is applicable to a geographic context, and if the approach can work across a wide range of site scales.

These scores were then tabulated into subtotals. Using the 'cost' criterion as an example of how this was applied, if an approach required minimal time or capital investment then it was scored a +2, if some time or minimal capital investment was required to carry it out then it scored a +1. If it required a specialist piece of software or an investment in software training then it was scored a -1, and if there were significant cost barriers such as outsourcing or niche skill acquisition then

it was scored a -2. We can see that with the SAD method, since it requires usually three or five sheets of paper and some site observation time, it scored a +2. Conversely, Data Storytelling usually required outsourcing the work or a high expertise in working with HTML5 or coding hence a score -2.

The matrix evaluation indicates that analogue approaches such as the SAD method and the Overlay Method are very cost-effective and highly useable, however highly-processed digital approaches, such as Data Storytelling and Data Sensory Perception, have more capacity to deal with big data.

	Big Data Criteria				Professional application criteria				
	Volume	Variety	Velocity		Cost	Use	Geo-	Scale	
SAD method	xx	x	xx	-5	√√	√√	√	x	+4
Overlay Method	x	x	x	-3	√√	√	√	√	+5
Geodesign	√√	x	√	+2	x	x	√√	√√	+2
DAD	√	x	x	-1	√	xx	√√	√√	+3
Data Visualisation (Tufte)	√	√	x	+1	√	√√	x	√	+3
Data Visualisation (McCandless)	√√	√√	x	+3	√	√	x	√√	+3
Data Storytelling	√√	√√	√√	+6	xx	xx	√	√	-2
Data Sensory Perception	√√	√	√√	+5	xx	x	x	xx	-6

FIGURE II: Matrix evaluation

When the approaches are weighted, as in Figure 12, within the criteria of the V's of big data, the prominent approaches used within landscape architecture score much lower than approaches from outside such as Information Design (both variants) and Data Storytelling. However, the three landscape approaches scored well when the last four criteria were applied. This could explain their popularity amongst landscape architects and why other approaches haven't been explored or developed.

3.3 Summary

From this literature review, there are some data analysis approaches that could be used with big data, but not one single approach addresses the increasing volume, variety, or velocity of big data as well as being applicable to landscape architects. Existing approaches used by landscape architects rely on 2D plans or 3D models built up through layers of geographic data and lack the ability to analyse the data in an explorative, interactive and visual way. Human cognitive processing power responds well to this and can perceive complex relationships better if data is presented appropriately (Mazza, 2009).

	+/-		
	3 V's	App.	TOTAL
SAD method	-5	+4	-1
Overlay Method	-3	+5	+2
Geodesign	+2	+2	+4
DAD	-1	+3	+2
Data Visualisation (Tufte)	+1	+3	+4
Data Visualisation (McCandless)	+3	+3	+6
Data Storytelling	+6	-2	+4
Data Sensory Perception	+5	-6	-1

FIGURE 12: Matrix evaluation – summary and totals

The literature review revealed a lack of discussion of how to analyse big data for landscape architects or site designers. It raises the question about the role of ‘data analysis’ and whether it is widely accepted within the profession as a part of the design process. There is a sense that it is perceived as too rigid, too scientific, or not innovative and creative enough for a design profession. This tension between the designer’s knowledge and ability to be innovative, versus the perceived scientific and objective data analysis, was also noted by Shen and Long (2015).

critique and matrix evaluation I have identified two approaches from within the existing landscape architecture theory that scored highly, and one from outside that scored highly. The three that will be applied are the Overlay Method, Geodesign and Information Design.

As stated in the Methods chapter, three data analysis approaches will be selected and applied in the case study site, and through the

	+/-		
	3 V's	App.	TOTAL
SAD method	-5	+4	+0
Overlay Method	-3	+5	+3
Geodesign	+3	+2	+5
DAD	+1	+3	+4
Data Visualisation (Tufte)	+2	+5	+7
Data Visualisation (McCandless)	+4	+3	+7
Data Storytelling	+6	-2	+4
Data Sensory Perception	+5	-6	-1

FIGURE 13: Selected data analysis approaches highlighted

4.0 Case Study: Waitangi Park, Wellington, New Zealand

4.1 Data Collection

Waitangi Park, a 6.5 hectare urban park located on the Wellington waterfront, was selected to be a case study site for this dissertation (Figure 15). It was chosen due to its high public profile, being an example of sustainable landscape architecture, well-established (built 10 years ago), a civic project commissioned by local government, and the potential for collecting a large amount of data. It was also selected as it was a site that I do not know well, helping to ensure that I wasn't influenced by my own local knowledge in data collection.

Data was collected over a three month period, from known online sources, searchable online sources and were all freely available for download. The data was downloaded in file formats which were primarily easy to import into ArcGIS, for example Shapefiles or Geodatabases, as well as Excel files, Comma Separated Value files (CSV), and finally as PDF files if no other file format was available.

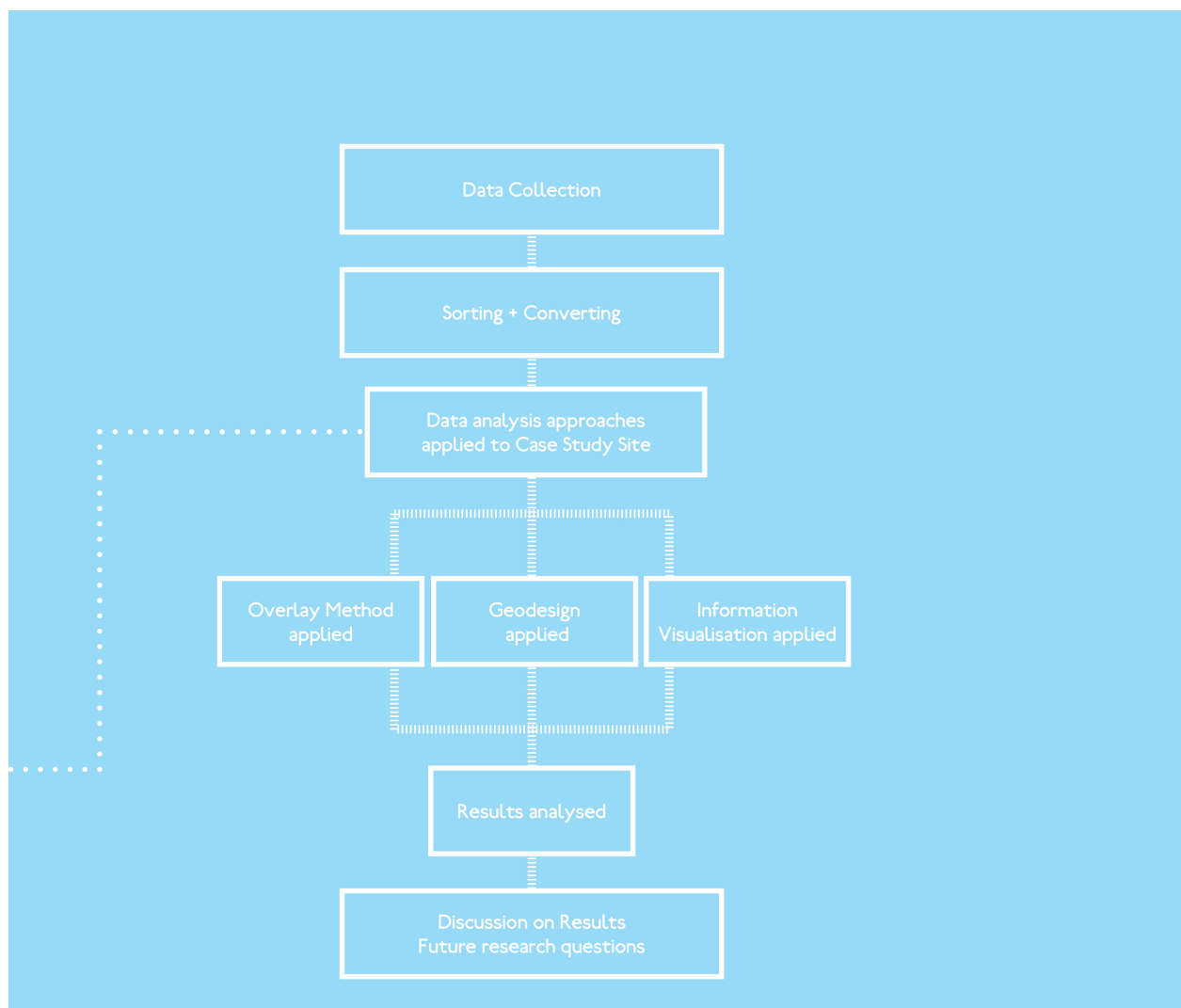


FIGURE 14: Process followed in data stream

IMAGE REMOVED DUE TO COPYRIGHT

FIGURE 15: Care study site (outlined in red) within its central Wellington context.

Image: Google Earth

As the data collection began, a significant amount of data was being gathered, but there was no direction to it. As I was keeping track of what was coming in, there was no way of knowing what data I was missing or had overlooked. Apart from my own understanding

The United Nations Economic Commission for Europe's (UNECE) Task Team on Big Data formulated a classification of types of Big Data in 2013, which proved to be a good starting point, but it lacked any detail under the category of data supplied by public agencies. As the New Zealand Government has moved to making more Open Data available, this category needed to be more robust, so the categories from data.govt.nz were meshed into

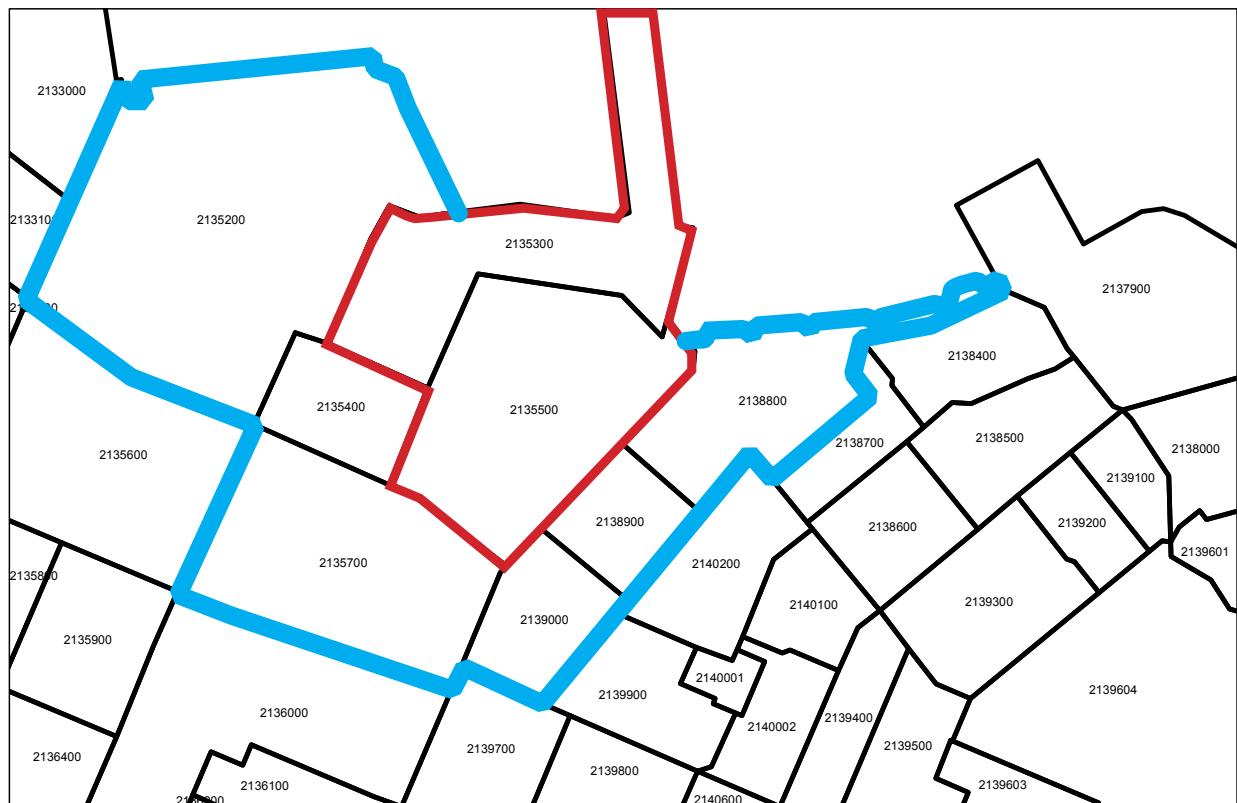


FIGURE 16: Case study site meshblocks (red boundary) with surrounding meshblocks (blue boundary)

the UNECE classification types (Figure 17). The results table was then used as a guideline to target categories that had no data, ensuring further veracity to the data.

	COUNT
100. Social Networks (human-sourced information):	
1100. Social Networks: Facebook, Twitter, Tumblr etc.	
1200. Blogs and comments	
1300. Personal documents	
1400. Pictures: Instagram, Flickr, Picasa etc.	
1500. Videos: Youtube etc.	
1600. Internet searches	
1700. Mobile data content: text messages	
1800. User-generated maps	
1900. E-Mail	
200. Traditional Business systems (process-mediated data):	
2100. Data produced by Public Agencies	
21001. Agriculture, forestry and fisheries	
21002. Arts, culture and heritage	
21003. Building, construction and housing	
21004. Commerce, trade and industry	
21005. Education	
21006. Employment	
21007. Energy	
21008. Environment and conservation	
21009. Fiscal, tax and economics	
21010. Health	
21011. Infrastructure	
21012. Justice	
21013. Land	
21014. Local and regional government	
21015. Māori and Pasifika	
21016. Migration	
21017. Population and society	
21018. Science and research	
21019. State sector performance	
21020. Tourism	
21021. Transport	
21022. Ministers, cabinet and portfolios	
2200. Data produced by businesses	
22100. Commercial transactions	
22200. Banking/stock records	
22300. E-commerce	
22400. Credit cards	
300. Internet of Things (machine-generated data):	
3100. Data from sensors	
3110. Fixed sensors	
31101. Home automation	
31102. Weather/pollution sensors	
31103. Traffic sensors/webcam	
31104. Scientific sensors	
31105. Security/surveillance videos/images	
3120. Mobile sensors (tracking)	
31201. Mobile phone location	
31202. Cars	
31203. Satellite images	
3200. Data from computer systems	
3210. Logs	
3220. Web logs	

FIGURE 17: Proposed categories of big data

4.1.1 Sources

Data was collected from as wide a range of sources as possible to ensure variety, with all of the data coming from online sources. There is scope for future data collection to make use of collecting one’s own data from the site / area using sensors or by other means, however for this case study, these were not explored, owing to the time and resource limitations of a dissertation. Figure 18 shows the major category sources of data.

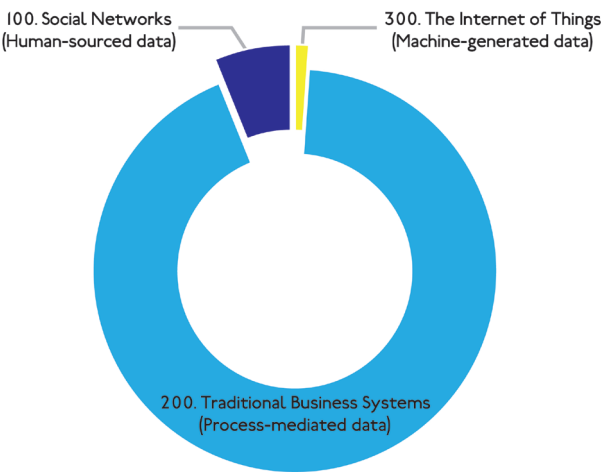


FIGURE 18: Summary of major category sources of data for case study site

When data was not available, there was also the option to submit an Official Information Act request to a Government Agency in order to obtain this data. Under the Official Information Act 1982, agencies are required to respond to any such request within 20 working days and must be released to you unless there is a good reason, for example it would be too onerous to or it may contain information which is under the Privacy Act 1993. After assessing the variety of the data from the various categories, I noted that I had no crime statistics at a fine grain, only data for the Wellington City region. After finding this gap, I could have submitted a request but as this dissertation seeks to answer questions related to practising landscape architects and designers, this avenue were not pursued.

There were other datasets identified that were not available, for example real-time data for Wellington bus services which include travel time, stopping time etc. However, a previous an Official Information Act (OIA) request submitted through fyi.org.nz to the Greater Wellington Regional Council was deemed to be too exhaustive to collate and distribute (Hastie, 2015). Another example included a request for CCTV footage from rail stations to the Greater Wellington Regional Council and the response was given that data from the CCTV camera system on the rail network was typically only kept for 14 days, but depended on how much

space was on the hard drive (Hastie, 2014). In these two datasets we see that data is created but not always available in a useable or readily accessible format.

A rich data source is of course – Social Media. I examined the following social media sources: Twitter, YouTube, Facebook, Tumblr, Flickr, Instagram, Google, Picasa, Vimeo and Blogs. I expected to be flooded with data but found that there was a limited amount of data available. There are several reasons for this. First, Facebook is a social network platform and requires access to a user's posts only if they allow it. This greatly restricts the access but by using the hashtag filter #waitangipark, I was able to see posts that had that tag applied then exported these results as a PDF. Facebook was able to display that 5,200 visits had been logged or tagged to this location, however the raw data of this which could reveal time and date, was not available. Second, the use of geolocated social data is limited. An example of this is demonstrated in the screenshot shown in Figure 19 which displays geolocated tweets from around the world in real-time. New Zealand is most notably not well represented when compared to Europe or the Americas and remarkably there were as many geolocated tweets from Tanzania as there were from New Zealand. And third, mining the data from these was time consuming. I could find no freely available tools to make this task more efficient,

and relied on my own use of a spreadsheet or PDF export.

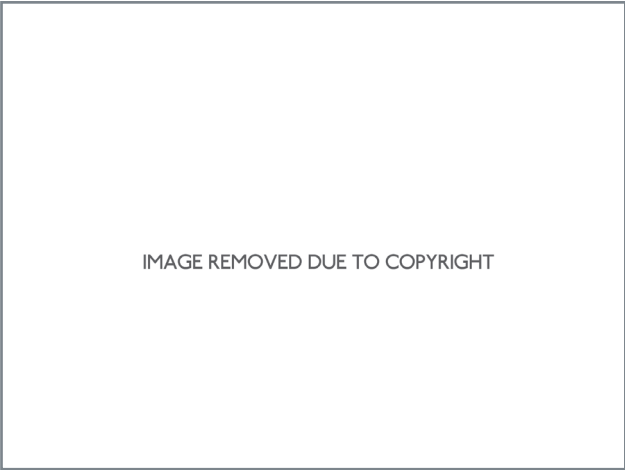


FIGURE 19: Map of geolocated tweets.

Source: Zajdband (n.d.)

Twitter was another difficult data source for me to access, and tweets that included the hashtag #waitangipark were not all visible via twitter.com. Instead, I resorted to a website, Backtweets.com, to see and export archived tweets as a PDF.

Social media is an important dataset to engage with and analyse as it not only provides a way to see frequency, date information and timing, it also reveals users’ behaviours (Abdesslem, Parris & Henderson, 2012).

YouTube was one social media source where I successfully engaged a workflow for collecting results. This workflow began with a Boolean search in YouTube for “Waitangi Park”. The

results were then exported using a Firefox browser add-on called SEOQuake as a Text file, then these were brought into an Excel spreadsheet, then the .xlsx file was opened in Screaming Frog SEO Spider 5.1. This application ran a process where it gathered all the metadata for each of the YouTube videos and then exported it into a .csv file which was then formatted appropriately and finally saved as an .xlsx Excel file.

Near the end of the data collection phase I realised that although I had obtained a number of datasets from the Population and Society category, I knew that the Social Deprivation Index would be an important and useful dataset. I deliberately sought it out, even though it did not appear in any of the major searches I did. At the end of the three month data collection period I was still stumbling across more datasets and could have continued to collect more but had to set a point at which to stop.

4.1.2 Format

Datasets were collected in their provided formats and sometimes this was conveniently either as .csv files or as georeferenced shapefiles, less conveniently as a PDF, or least conveniently as a non-exportable webpage or online database. The first two file types were preferred as they were easily applied with

the data analysis approaches: .csv files can produce charts or tables in Excel or Tableau and georeferenced shapefiles can be directly imported into a GIS software program. The format types are graphed in Figure 20.

Some datasets were only available as non-exportable online databases. One example of this was the land value data for the properties

within the meshblock areas, as this was only available as a searchable result from the Wellington City Council website (<http://wellington.govt.nz/services/rates-and-property/property/property-search>), with each property searched, results were then entered into an Excel spreadsheet (Figure 21). As there were 984 land and property values that had to be entered manually, it was a time consuming task.

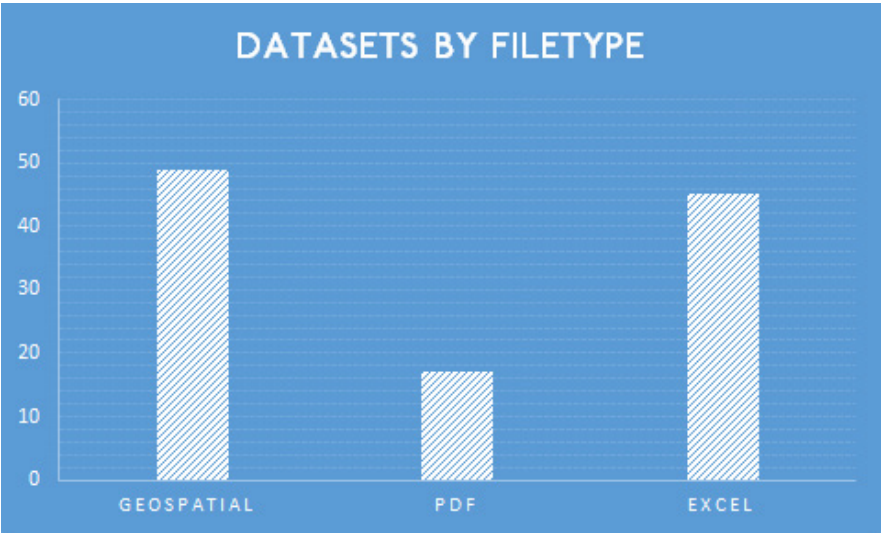


FIGURE 20: Summary of dataset format types for case study site

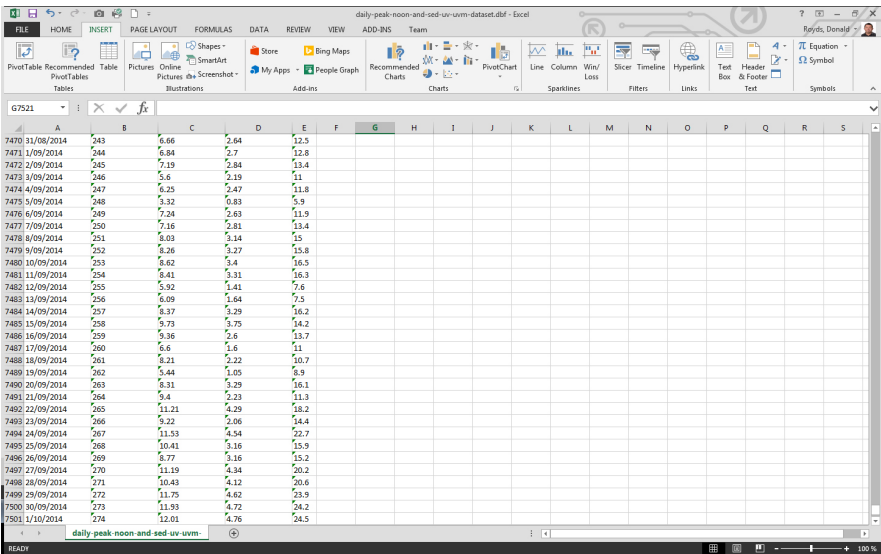


FIGURE 21: Sample of raw data in .csv format in Excel

This could have been avoided if the services of a company such as Quotable Value were used and depending on the costs involved this could be prohibitive to a user – but would still need to be added to a georeferenced shapefile manually.

Some datasets, such as the GeoNet earthquake dataset, were not easy to understand at first as I was unsure exactly what they contained, or how to use them, and it required going back to the original source to go through how it was formatted. This proved to be a time consuming but necessary task to ensure that I could apply this data to an approach.

Raw data was also not always obtainable for each dataset, and sometimes only summary data was provided by the source. An example of this was the Regional Visitor Monitor, provided by the Ministry of Business Innovation and Employment, where they collect a range of visitor information, including planning and booking, accommodation, transport, activities, and environmental perceptions, yet only supply this dataset as score totals across the country.

Real-time data, often gathered as machine-generated data, represents the velocity attribute of big data, and this category was an area where there was little to no data available.

The final comment on formats relates to the use of cells and spreadsheets. I used Microsoft Excel for many of the tasks in this phase but also found Google Spreadsheets were helpful as they provided alternative formulas that worked with online services such as Google or web feeds.

4.1.3 Summary

In summary, the data gathered during the data collection phase for the case study site was comprised of:

- 1.74 GB total folder size of raw and reformatted data;
- 111 individual datasets;
- 49 available as geospatial data
- 17 PDFs
- 45 Excel spreadsheets.

Big data was readily available for the case study site but there were a number of hurdles that were encountered during the process.

These hurdles included finding that the formats available were not always easy to use immediately and had to be manually entered or could not be added to a GIS program; some datasets were not available in full and a request to Government agencies would be required; and there were also limited software options for extracting social media data from their original sources.

The number of available datasets in each category (shown in Figure 22) demonstrates where the importance or priority has been placed in regards to collecting and distributing information within the Wellington context. There appears to be more data available in categories such as environment, infrastructure, and land whereas categories such as energy, education and health had relatively fewer datasets available.

Through this data collection process it was identified that there also needs to be a more structured set of categories of big data along with a robust way of collating and recording what it is that has been gathered. There needs to be clear categories to ensure a comprehensive spread over a range of areas to provide breadth, and a way of knowing what sources are available in each category to ensure a good depth to the data also.

Some of the data collected did not go down

in scale to just the case study site itself, for example New Zealand Police crime data, but it was useful as it provided a context for the other datasets and the site. Big data doesn't necessarily correlate to site data, but is certainly contextual data.

4.2 Application of data analysis approaches

Having now collected the data for the case study site, the next stage in the research process is to test three data analysis approaches for their efficacy.

Three data analysis approaches were selected from the literature review based on how well they scored in the criteria matrix and these were: the Overlay Method, Geodesign, and Data Visualisation.

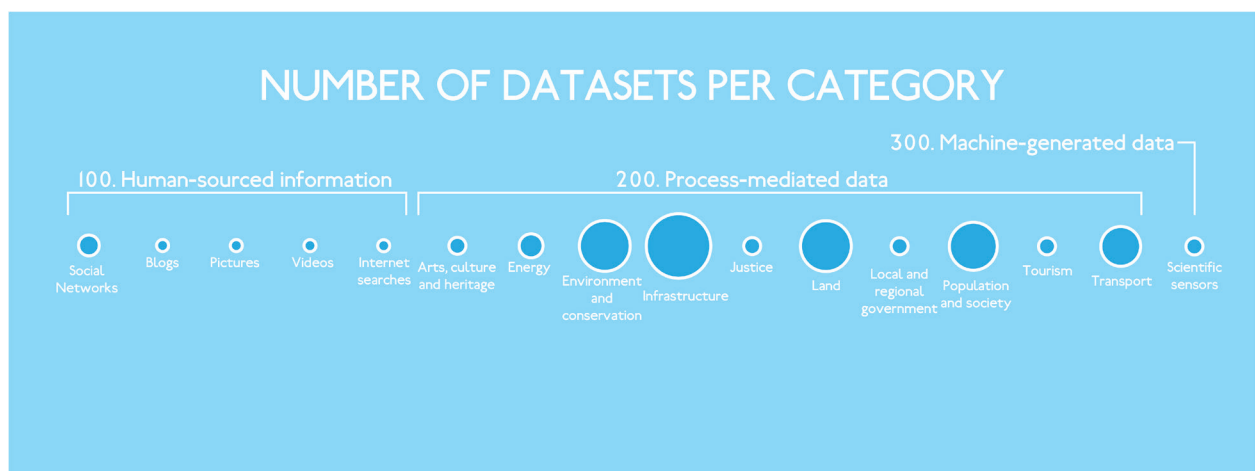


FIGURE 22: Number of datasets per category of big data found for case study site

The GIS software program ESRI ArcMap was the primary tool used in the collation of data the Overlay Method and for the Geodesign approach because of its ability to present site data, in particular basic mapping for the Overlay Method and for its processing tools for the Geodesign approach.

4.2.1 Overlay Method

The Overlay Method relies on maps which show discrete datasets or 'values' to be physically overlaid above each other, with the result showing areas where there are overlaps between them or gaps where the 'values' are not present. This method is a common

practice used by landscape architects as it has been used for teaching landscape architecture students (Turner, 2014). It is also an analogue process as the use of computers is typically left out of the analysis and I have only used software to construct basic maps.

Once the georeferenced shapefile layers were added into ArcMap, their transparency was reduced to 50% to aid the 'layering' process, then they were exported as PDF files and printed onto overhead projector transparency film. They were then overlaid into one 'stack'. This 'stack', as seen in Figure 23, shows that there is no useful result. The result was 'muddy', confusing, and does not appear to



FIGURE 23: Overlay Method result: 30 individual layers of data 'stacked'

reveal anything of use. I made a decision at the beginning of this approach that to ensure it doesn't stray into too much digital manipulation that no further colour changes or category 'symbolology' would be applied to the layers other than to change the transparency.

As this 'stack' contained 30 layers, I wanted to ensure that the integrity of the film itself was not a factor so placed it on top of a light table yet the result remained muddy. I then went further to separate out the 30 layers into layers of three groupings: line layers, point layers and area layers. These were then examined as individual groups but still the result was a map that revealed little about the data (Figure 24).

4.2.2 Geodesign

The Geodesign approach is synonymous with ArcGIS and so ArcMap was used for the application of this data analysis approach, following the workflow shown in Figure 25.

The first step was to work with the existing shapefile layers that had been used previously for the Overlay Method, the layers which had subcategories (such as values 1-9) were identified and given a colour gradient ramp to display these values in more detail.

Data was not imported into the Geodesign approach if it did not come already in the format required (such as .dbf or .shp). This demonstrated that pre-processing would be required to transform the remaining datasets into usable ones in ArcMap.

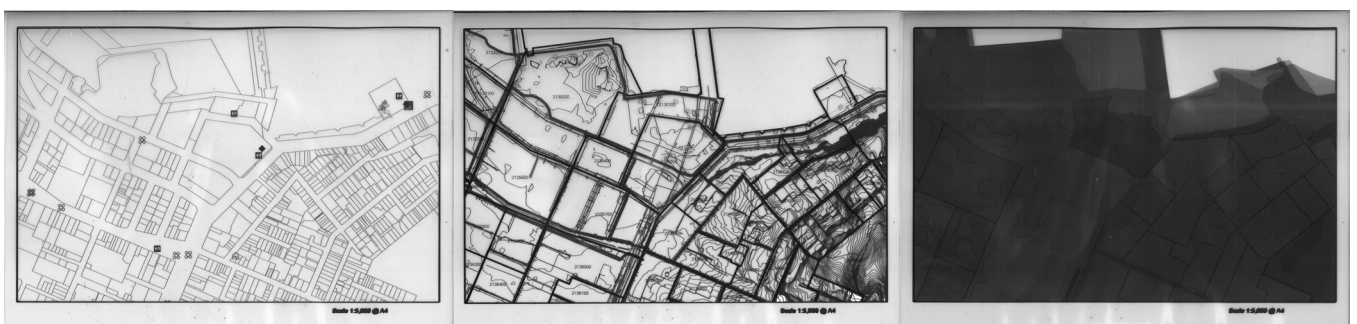


FIGURE 24: Overlay Method: Composite groupings using point, line, and area layers of data

In order to begin the data analysis, a series of questions that related to the data and the site were formulated to query the data. The questions that were used were:

1. What other amenities are within a five or ten minute walk of the site? (Figure 26)
2. Where are the surrounding open / green spaces? (Figure 27)
3. How many people live within a five minute walk of the site? (Figure 28)
4. What is the density of the buildings? (Figure 29)
5. Where are the areas at high risk from a natural hazard event? (Figure 30)

6. What infrastructure is at risk from ground shaking hazards? (Figure 31)

Once the questions were set, I then had to identify the relevant geoprocessing tools and workflow in order to achieve an answer to the question proposed.

IMAGE REMOVED DUE TO COPYRIGHT

FIGURE 25: Geodesign workflow diagram. Image: ESRI (2013)



FIGURE 26: Q1 - What other amenities are within a five or ten minute walk of the site?



FIGURE 27: Q2 - Where are the surrounding open / green spaces?

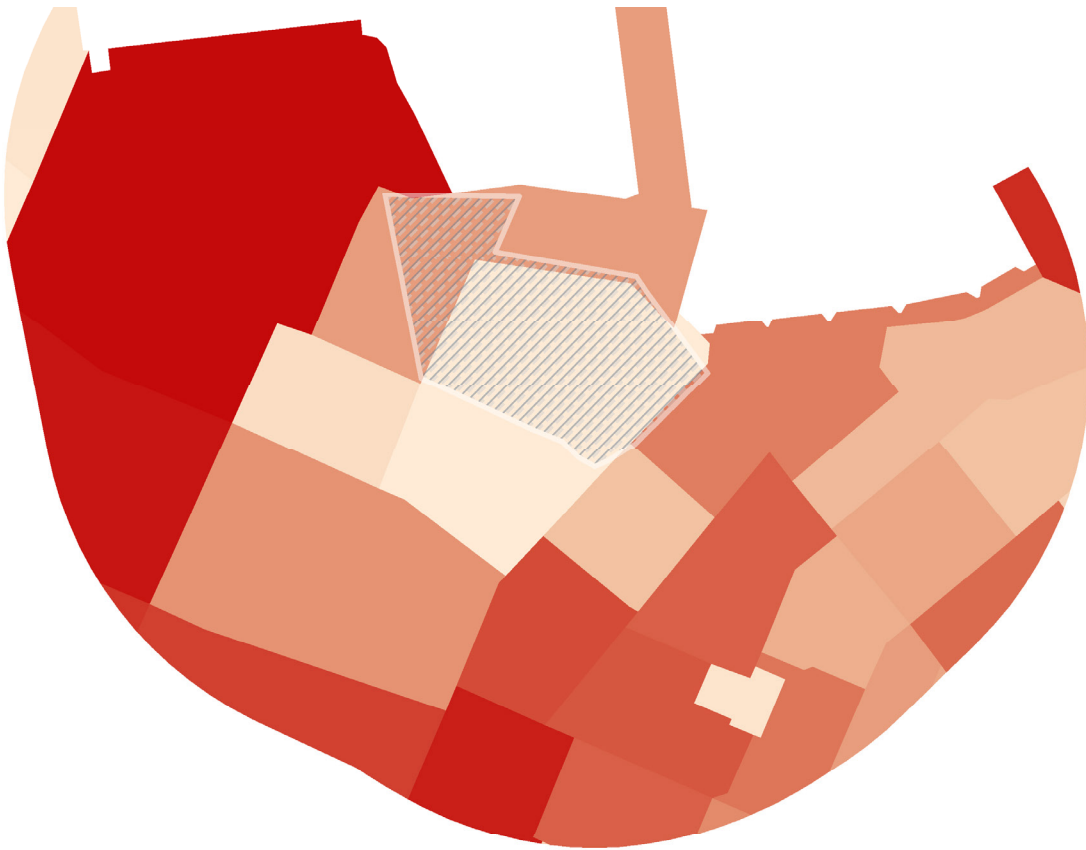


FIGURE 28: Q3 - How many people live within a five minute walk of the site?

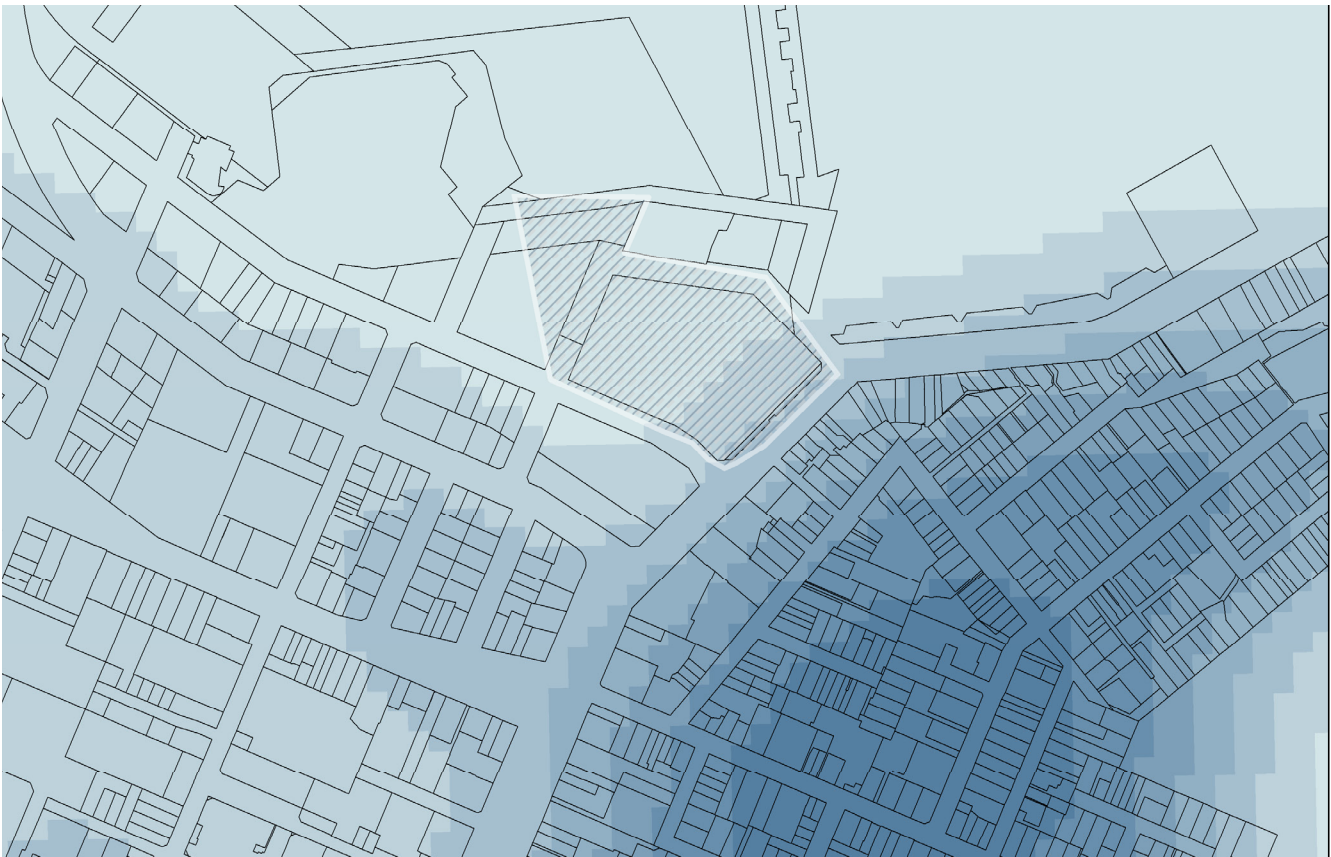


FIGURE 29: Q4 - What is the density of the buildings?



FIGURE 30: Q5- Where are the areas at high risk from a natural hazard event?

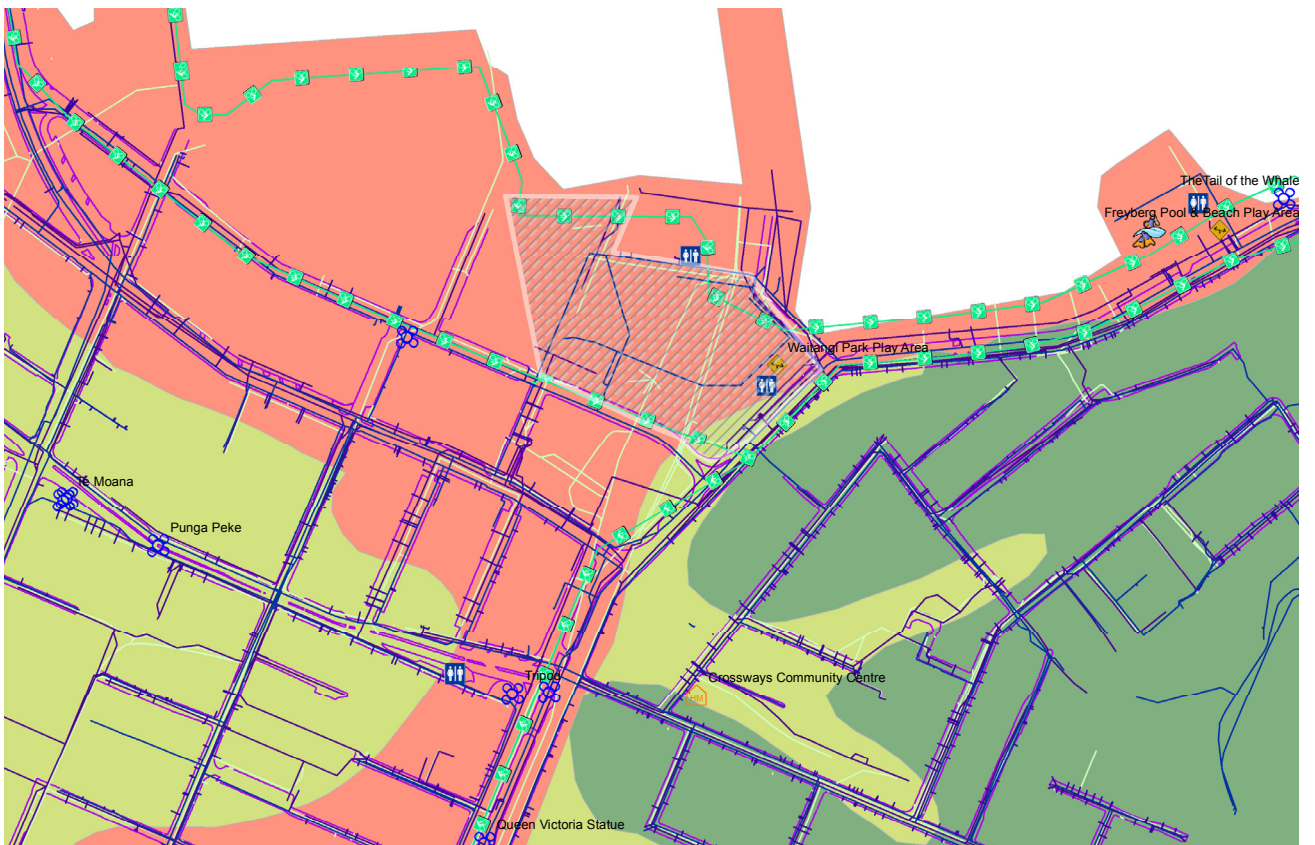


FIGURE 31: Q6 - What infrastructure is at risk from ground shaking hazards?

For question 1, 400 and 800 metre buffers were created from the site boundary and with all the amenity layers visible, this revealed which amenities were within a five minute walk radius (400m) or 10 minute walk radius (800m) (Figure 26). The Near Analysis Table tool also revealed the exact distances to each of these.

Question 2 required the least amount of additional analysis as the open space was visible on a single layer as a dataset. Land parcels and meshblock layers were added for context as well as the labelling of each open space.

Question 3 sought to identify the residents were concentrated within a five minute walking radius from the site. This could help to reveal possible circulation patterns and which routes larger volumes of users would use.

Question 4 had the most surprising result from the analysis. At first I thought it would be interesting to show density as site coverage by built forms but this could not be achieved with the current geoprocessing tools (that I could understand), but then the next option to show density was to look at how many buildings, regardless of size, and within an area. The geoprocessing tools used were 'Feature To

Point', which converted the building footprints to points, then Point Density to then calculate and visualise the density of building points per square kilometre. The result showed that building density increased in the direction of Mount Victoria to the south east of the site. This is likely due to the high demand for the views that such a location affords, along with the age of the buildings in the area being older (and naturally smaller). Buildings closer to the city centre were larger but contained more apartments and retail shops hence the lower building density.

Question 5 required me to identify which natural hazard layers could contribute to high-risk factors, and with experience from the Canterbury earthquake sequence of 2011-2012, the most relevant earthquake layer was deemed to be the ground shaking layer, and this was then layered with the flooding hazards. As this was still not the clearest way of showing where the highest risk areas were, I used the Intersect Tool to show where the highest ground shaking and flooding hazards would be likely to occur, then turned on the property boundaries layer for context (Figure 30).

Question 6 was another natural hazard question which relates to the lessons learnt from the Canterbury earthquake sequence. The lesson from this event was that infrastructure such as road, pipes and kerbs, were damaged more by liquefaction than by the ground shaking itself. So to answer this question I made all the infrastructure layers visible (kerbs, storm water pipes, wastewater pipes, water network, water service pipes, amenities and cycle routes) and made the liquefaction layer visible. The liquefaction layer had three levels of risk associated so red was applied to the highest risk of liquefaction, yellow to medium risk, and green to the lowest risk of liquefaction. The resulting map (Figure 31) reveals that most of the waterfront (reclaimed land) and its associated infrastructure, is at a high risk of damage during an earthquake event.

At the end of the data analysis there were six maps produced which provided a geographical understanding for the topics covered by the original six questions, along with a working GIS file which could be further scrutinized. Had a design brief or client been part of this process, it could have provided further direction to question of the data.

4.2.3 Data Visualisation

The workflow that I followed for applying the Data Visualisation approach was to first go through all the available data by reading the rows and columns of data or text of a PDF file. I then went back through the data to review all the terminology and attributes and investigate these items further from their sources if I did not feel I understood them and their context. Next I used Excel or Tableau to interrogate the data through interim charts or graphs, and cognitively processed the lines of information looking for patterns or items of interest. These were then summarised and presented graphically as an Infographic.

This data analysis approach proved to be the most challenging for me to apply – not because of its complexity but because it used a process I had not been exposed to before. Despite experts in this area such as McCandless, Tufte and Yau writing extensively on this topic, there was little guidance to suggest a standard process to follow and this meant that the process I ended up following was an organic, explorative one.

This approach relies on the cognitive processing ability of the brain to spot and associate patterns or trends in data that computational algorithms can't, but in order to do this, a great deal of time must be invested

in getting to know the data. Part of this time challenge is simply going through line by line in spreadsheets, but a large part I found was also deciphering and decoding technical classifications. For example, for the UV datasets provided by NIWA, the data was supplied in units of DUs or Dobson Units, and I then needed to understand what the significance of these units increasing or decreasing. What I was able to then find out was that 1 DU is equal to a 1 millimetre thick layer of ozone over a specific area in the stratosphere. This was useful as I could then understand the significance of a low DU measurement as I was able to compare it to the global average of 300 DU (Newman, 2013).

I explored different ways to display the data that was converted from YouTube metadata into an Excel file, and found that a simple iconographic approach worked to summarise the key, and amusing, data as shown in Figure 32.

I used Tableau to help me explore the datasets further than Excel could and I found it to be intuitive with limited practice. It did however require at least one common field to create a join between to datasets but did have features such as Data Cleaner which reduced the time required to reformat files.

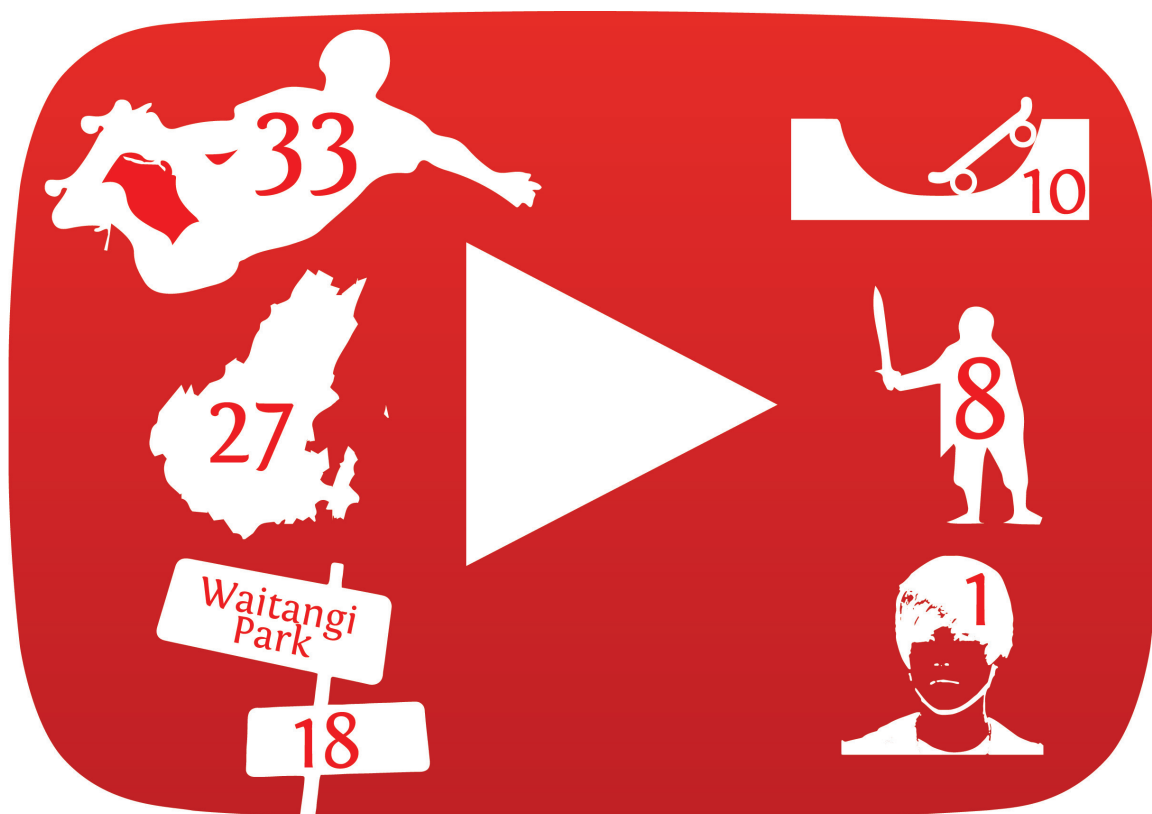


FIGURE 32: YouTube Infographic created from keyword metadata

One process which I had not come across, but instinctively came up with was to take all the keywords that people used keywords to describe themselves from a dataset (Litmus, 2011), then put those into an image search and then the images which were tagged of individuals were collated into a single image (Figure 33). This final image revealed who the site users might be, without requiring me to take photos of actual users.

Taking all the minor graphs, graphics that were produced throughout the process, along with other patterns of interest, I summarised and combined these into one final data visual using a template developed by Yau (2011) as shown in Figure 34. Further refinement of this process would be beneficial and level of graphic understanding would be required to gain maximum effect. The final result however does provide the viewer with a 'dashboard' of sorts, with a variety of information available in one glance, which can then be investigated further.

4.2.4 Summary

The Overlay Method, while widely practised, does not have the capacity to work with big data. This was demonstrated by adding only 30 layers of information with no usable outcome, being obscured through physical stacking, and when the layers were separated out into the layers with point and line data it was almost just as illegible.

As data layers were added to ArcMap, the datasets that contained more than one category or field had their symbology displayed as a red to green colour ramp which helped to identify any compound effects, especially as each area dataset had a transparency of 50%.

A weakness in the Geodesign approach is that in order for any analysis to begin, there needed to be an appropriate set of questions that required answering. While this does provide a starting point, it can overlook other patterns that are not apparent and narrow the analysis too quickly.

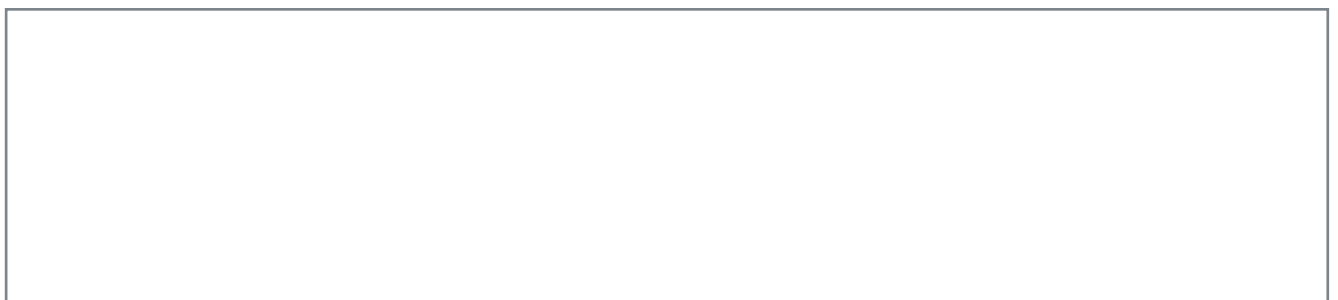
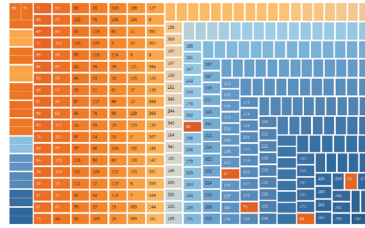


FIGURE 33: Faces of Wellington: how users of the area describe themselves

WAITANGI PARK INFOGRAPHIC



49%
of the year, the
Ozone layer is
less than the
global average

**NZERS USE GEOLOCATED
TWEETS AS MUCH AS
TANZANIANS**

Unrestricted Dog
exercise areas

86%

Crime is down

65%

Average Age

35

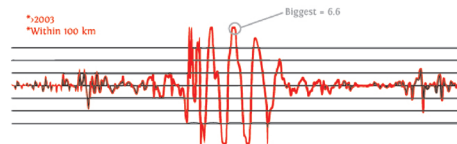
85%
in upper 50%

15%
in lower 50%

Socioeconomic Deprivation

**5,700 VISITS LOGGED VIA
FACEBOOK**

PEOPLE WHO WORK IN THE AREA...



140 Earthquakes



FIGURE 34: Site Infographic (based on Yau, 2011)

Although software programs and open source software was used, no coding or scripting was used as this would not usually be an expected skill of a landscape architect.

Methodically going through a lot of technical jargon slowed down the analysis of the data under the Data Visualisation approach as there were some very specific codes and classifications to comprehend. This was an exploratory process and there were many new areas that required an investment of time – which could be an obstacle in applying it in a working environment. It did however provide an approach that could include more geospatial and non-spatial data than the other two approaches.

5.0 Discussion

Each of the three data analysis approaches had their merits.

The speed by which the Overlay Method could be applied was a positive and results were achieved in the shortest time out of the three approaches. It was intuitive, and placing the layers into stacks or groupings was an engaging part of the process— even if the result meant that not much sense could be made of it.

As this approach was intended to be analogue, and because the output was too unclear, there was no further meaningful or useful analysis that was achieved from this approach with the layers obtained.

I reached a similar conclusion in a recent project looking at a Structure Plan for Central City North (Christchurch), as part of a studio project in the taught masters (LASC 617). In this project I looked at five layers of data and what role hierarchy played. The location of a layer in the stack was directly related to how visible or prominent that value would be and that by rearranging the layers, different information would become more either hidden or seen. For example, in Figure 35 the layers of land condition, hydrology, green space, social deprivation and movement were arranged in that order (left), however, when that order was reversed there was very different hierarchy to what was now visible (right). The original order revealed more about landscape systems and

less about people, whereas the reversed order showed more about people than landscape systems. How the order was arranged bore greatly on which data was used to inform site-based decisions.

Geodesign was able to deal with both a large number of datasets and datasets with large data, but could still only work with geospatial data. To include the variety of datasets that big data is available as, would be an area for improvement. It should be noted though, that there is constant improvement in the

software, hopefully to cover this obstacle as well as incorporating multiple file type inputs. GeoEnrichment is the latest advancement, albeit still in its early stages, where there has seen some movement towards melding geospatial and non-spatial information (Figure 36). It aims to incorporate statistical data with the 'map view' but does so in a crude and disjointed way. This attempt to pair non-spatial data with geospatial data is not convincing.

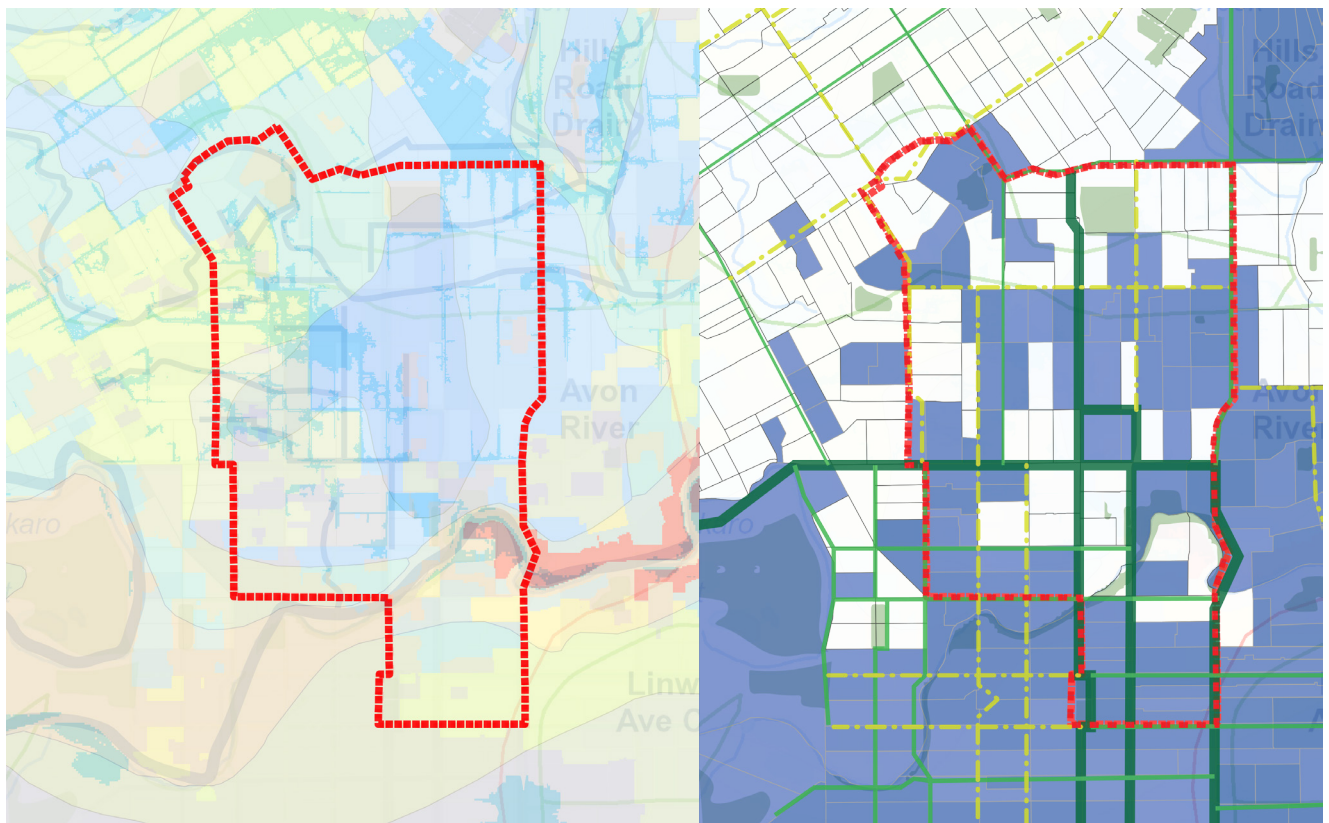


FIGURE 35: LASC 617 layers – original order (left) and reversed order (right)



IMAGE REMOVED DUE TO COPYRIGHT

FIGURE 36: An attempt to pair non-spatial data with geospatial data - GeoEnrichment.

Image: ESRI (2013)

Specialist computer programs were not featured in this case study as it was decided to keep this process as close to what would be carried out in landscape architectural practice as possible. Microsoft Excel was used extensively and since it is common in most offices around the world this piece of software will be the most accessible. Also used was the incorporation of GIS software with ArcMap for both the setup of the Overlay Method and for carrying out the analysis within the Geodesign approach. There was the reliance on my own prior knowledge and investigative judgment as to which geoprocessing tools were available within the program to answer the questions effectively. There currently is a limited set of tools available and there are gaps which require work to close (Miller, 2012). Tableau Public and Adobe Illustrator were also used

in the preparation of graphics for the Data Visualisation approach.

One aspect of the case study which I had underestimated, was the time required to read through and 'know' the data. This was of course a large component of the Data Visualisation approach and it was required for each step of the process as this was my first foray into obtaining big data instead of traditional site data collection methods and this required more time to learn. This time was necessary to understand the data: how it was collected, how it was formatted, and what the technical classifications meant. This could not be part of an automated process as it would have limited my ability to engage with the data and rely on cognitive processing.

It could be argued that the order in which these three data analysis approaches were carried out could have produced different results, for example, if the Data Visualisation approach was carried out before the Geodesign approach then perhaps I could have been more aware of the data and have asked either more specific questions or that the questions could have probed the data deeper. Regardless, it was apparent from this case study that more patterns and relationships were revealed in the Data Visualisation approach than in the other two approaches.

The Data Visualisation approach relied on personal discernment and judgement; to see what I saw or to see what I 'wanted' to see. On the positive side, this allows for customisation in response to a brief. However, there is also a potentially negative dimension in that it has the potential to be manipulated for a particular bias or for someone to make selective interpretations. Regardless, it was a creative and stimulating process to undertake. I began to see the data in new ways and thought laterally about not just how to show what I had found, but how it could be viewed from another angle or reveal its significance.

At the conclusion of the case study I felt very connected to the site and surrounding area. I did however feel that I couldn't fully absorb many of the datasets as there wasn't a context

of how they compared to other regions within NZ, and had this comparison been included then it might have helped. The connectedness that I did experience though could have been amplified if I had visited the area or knew it well before starting the data collection and analysis as it could have directed me to search or collect data based on observed / perceived nuances of the area.

Had this case study been applied to a specific project with its own design brief, then particular data could have been requested or obtained in order to align with the requirements of a designer or client, but this was not the situation for this case study.

The physical handling and storage of the collected big data was not a difficult task as the total data collected for the case study was 1.74 GB – which was easily stored on a USB pen drive and in a cloud-based service (Dropbox.com).

Beyond the data collection phase, I found that I was constantly stumbling across new sources of data, which I wished I had known about earlier but couldn't now include – for example CliFlo which is the National Climate Database. This also reinforces the notion that the collection and analysis of big data could be more efficient as the task is repeated.

Big data could be part of a useful discussion within the education of landscape architecture students by demonstrating how exploring data analysis methods through visual representations, it could lead to an improved understanding of a site and its context, and could inspire sustainable and creative design process.

5.1 Summary

The Overlay Method is not suitable for big data – unless it is broken down into lots of grouped maps – and does not facilitate a robust understanding of the data.

Geodesign is suitable for big data – but only geospatial data. It presently cannot deal with anything that does not have coordinates. If the right questions were asked, and if the geoprocessing tools exist, then the results can be useful.

Data Visualisation is suitable for big data – but it does require an investment in time. It can convey large amounts of data quickly or just the 'juicy bits', and has the potential for the misrepresentation of data through individual interpretation. It has some scope for working with both geospatial and non-spatial data.

To conclude, there was no clear approach that dealt with big data sufficiently or with an

acceptable efficiency, and it is evident that a different or hybrid data analysis approach is needed to incorporate both non-spatial and geo-spatial data.

This gap will be discussed further in the next chapter.

6.0 Mind the Gap

As previously identified, there is a gap between the two most applicable data analysis approaches – Geodesign and Data Visualisation – and there is currently either a weak or non-existent bridge over this gap, as shown in Figure 37.

There is no doubt the temptation to simply ‘slam’ the two approaches together, such as the GeoEnrichment platform does, does not provide a sufficient answer as it relies on machine processing, as Mazza (2009) has already shown, is best achieved through human cognitive abilities. The immersing of the user into the data is also fast-tracked and it is not clear how limiting this could be to understanding the data.

The role of data visualisation, particularly Infographics, is more prevalent with how Statistics New Zealand provide some of their summary data. Not only do they produce more interactive datasets (Figure 38) but also in the form of infographics, such as Figure 39, where summary data has been used in 50-year blocks for Wellington city.

There is more scope for the use of interactivity and real-time input for bridging this gap, but this could dilute the efficacy of the infographic which works best when all of the summary data visuals are displayed in one combined area – as opposed to hiding away waiting for a mouse click or mouse hover. Cheshire and Uberti discuss interactivity when they looked



FIGURE 37: The Gap

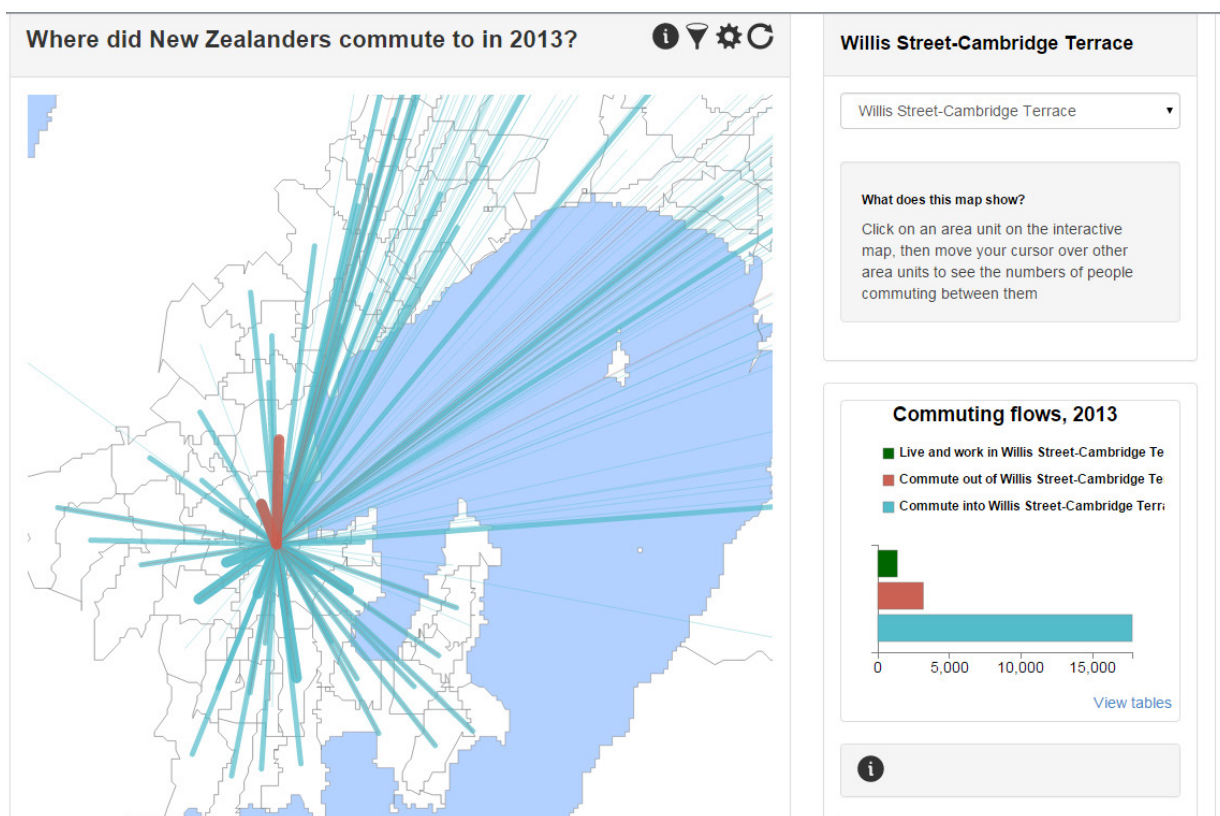


FIGURE 38: Statistics New Zealand make use of an interactive data visualisation to show journeys of Wellington commuters. Source: <http://www.stats.govt.nz/datavisualisation/commuterview/index.html>

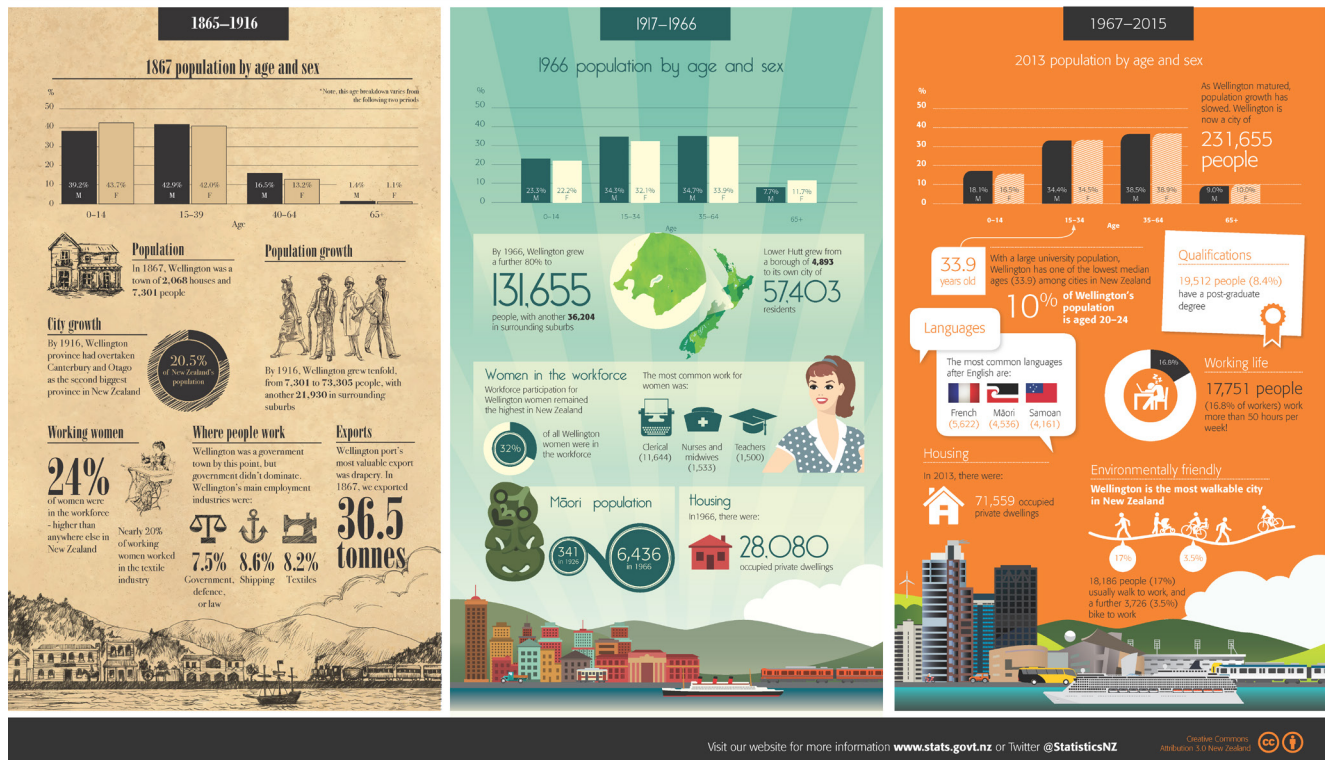


FIGURE 39: Statistics New Zealand Infographic to show 150 years of Wellington statistics.
Image: Statistics New Zealand (2015)

at making their data visualisations interactive and their conclusion was “you can simply see more at a glance on a printed page than you can pinching, tapping and scrolling on a smartphone screen” (2014:28).

We could look to blur the two ends of the spectrum perhaps. Could Geodesign become more infographic? This has certainly been the aim of the GeoEnrichment application. Can infographics become more geographic? Could there be a way to blend the two but still maintain the ability to adjust the balance so

that on one project it could be more spatial and less infographic?

There are also many small software-related tools for analysing and visualising data. This is something others may wish to evaluate, e.g. Google Correlate, Google Refine, Ruby scripts within browsers, d3.js and InfoVis which are JavaScript-based toolkits. Anselin, Syabri & Kho (2006) have put forward a program called GeoDa and proclaim that it has the ability to be the display of both qualitative and quantitative data. Old (2002) proposes that the

use of ‘substrate’ can transform geo-spatial into spatial information and would help span the qualitative – quantitative divide. DeLyser & Sui have even gone so far as to suggest that Lefebvre’s idea of rhythmanalysis “can help cross the qualitative – quantitative chasm by connecting multiple scales, senses, and domains” (2013:299). There could be some investigation into this idea, particularly in geographic research, yet we still to move away from formulas and set processes to look at data and “let the dataset change your mindset” (Rosling, 2006).

Landscape Urbanism proponents often present experimental graphics that attempt to lean across from both sides of the gap, albeit only as part of the presentation phase. As demonstrated in Figure 40, a graphic produced by Corner & Allen (2001) for Downsview Park, Toronto, displays maps and layers in the same space as non-spatial information such as flora-fauna relationships and temporal transitions.

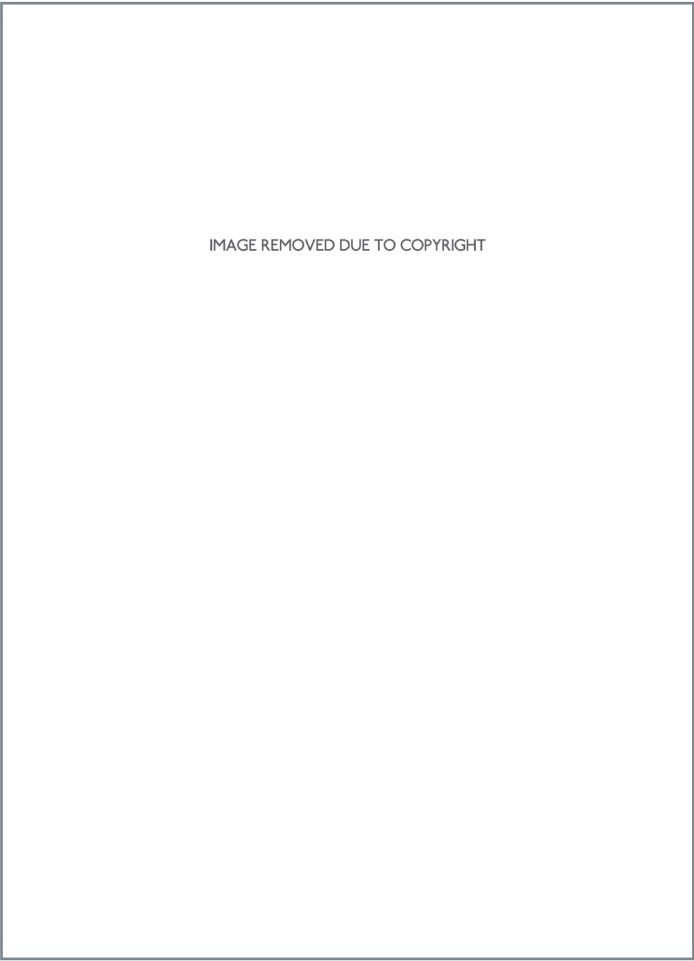


FIGURE 40: Landscape Urbanism graphic showing use of spatial data and data visualisation.
Image: Corner & Allen (2001)

There has also been a discussion on whether data visualisations and infographics are dead (Gifford, 2013), while others think that these have moved on and become more corporate (Wilson, 2015). For others, data visualisations are very much alive and will forever be relevant forms of communicating data (Windels, 2015; Hughes, 2015).

A possible way forward could be the idea of a dashboard – much like the inside of a cockpit where all the relevant and important information, along with relationships and patterns, are clearly and quickly visible. Further investigation into a particular point of interest could be carried out. It would be advantageous, as mentioned earlier when discussing interactivity, as all the information would present in one discrete area. It could

however disadvantage a user by overwhelming them if they were using it for the first time, or if they preferred to go through the data in small, bite-sized pieces. Perhaps the means by which to work with this dashboard is more about the interface itself, whether it is a mix of digital and analogue, or 3D with the aid of a headset or Google Cardboard.

It could also be that the blending or combining of the two data analysis approaches is not the best way to think of finding a solution. The process of applying one approach followed by the other, as in my case study, revealed the merits from such a process and this is something that could be explored further, as shown in Figure 41.

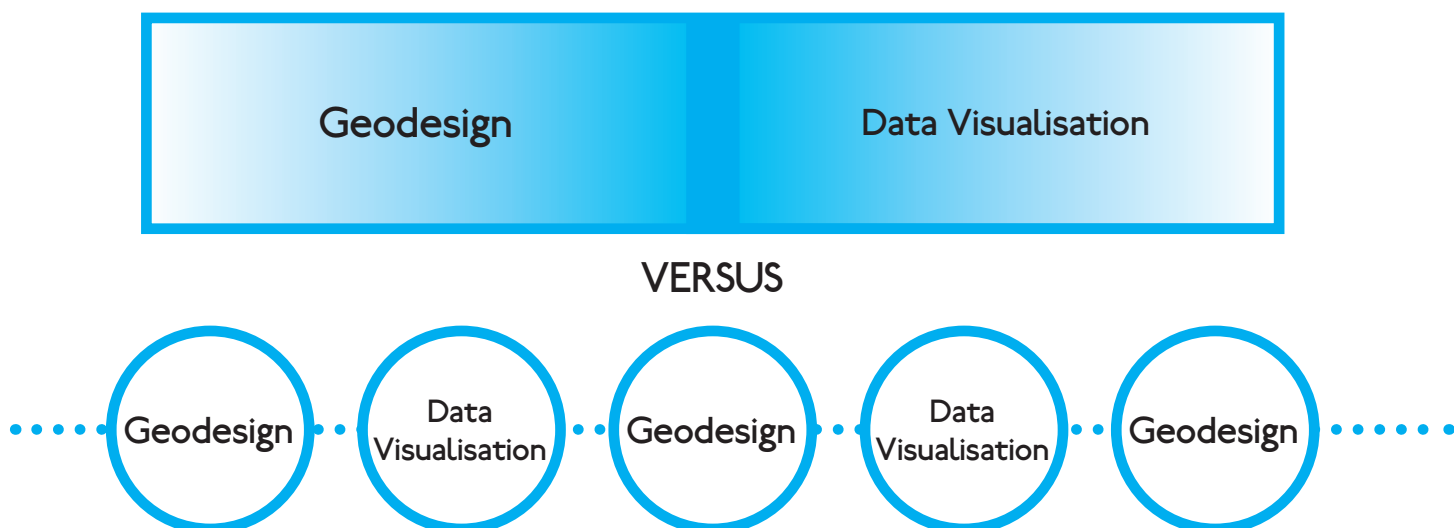


FIGURE 41: Geodesign and Data Visualisation combining versus an alternating process

Or we could teleport into the future with Novich
& Eagleman's vest and train ourselves to build
new senses – possibly even the 'sense of data'.

IMAGE REMOVED DUE TO COPYRIGHT

FIGURE 42: Eagleman wearing the vest which enables a brain to process encoded vibro-tactile information through the skin. Image: Eagleman (2015)

7.0 Conclusion

My research focussed on a case study site, Waitangi Park in Wellington. For this site I exhaustively gathered data, and then analysed it using three data analysis approaches: Overlay Method, Geodesign, and Data Visualisation. This investigation revealed a range of findings about big data, its analysis, and landscape architecture's current potential to deal with big data. As was demonstrated through a case study, there are approaches to analyse the large number of datasets available to landscape architects when working with a specific site (depending on scale and location).

The application of the data analysis approaches in this case study would be different if the study site was in another country where open data such as those from government agencies, was

not freely available.

Context was an observed advantage during this case study in using big data in landscape architecture. Site data can limit a landscape architect if the surrounding community and environment have not been included in the site's story that the data tells.

The Overlay Method was shown to not be appropriate to work with big data, and whilst the Geodesign and Data Visualisation approaches were not able to be complete in their analysis of big data, applying the two in a sequence proved to be a strategy which dealt with the dichotomy presented between geospatial and non-spatial data.

For landscape architectural practices there is the potential for a dedicated staff position, much like a data scientist but with a background in landscape, to specialise in this area to build up a company's knowledge and skillset more efficiently. This would more likely to occur within larger design offices, which are also likely to be multi-disciplinary – another area in which these skills are vital. Or perhaps as Walliss & Rahmann (2016) noted, it is time to expand the skillset of landscape architects to include data analytics, along with critical thinking, to engage with the big data.

Some of the questions which have emerged from this dissertation are:

1. Can the gap between the analysis of geospatial and non-spatial data be bridged effectively?
2. What are the risks for landscape architects in using big data?
3. Could the interface play a bigger role in analysing big data for landscape architects?

This topic of what tools are available for landscape architects to work with big data can be returned to when there are new techniques. A revisiting could also entail a survey of which approaches are popular and why, amongst practising professionals along with a review of the data analysis approaches plotted in Figure 10 and whether they can keep up with the

increase in the volume, variety and velocity of big data.

The big data categories and classification could be revisited in further research to ensure that they are robust and look to refine them as technology advances. Further research could also look into whether a user's efficiency in collecting and processing big data increases over time – to see if the user's time decreases for the task as they become more aware of how to work with the various sources, formats and workflows.

There are various software programs available, for free or for purchase, to assist with either the obtaining or analysing of the data. There were limited options for extracting or mining data from social network categories of big data but this could be revisited when more become available. Along with Tableau Public, there are a wide range of software programs or platforms for Data Visualisation, such as Google Correlate, Google Refine, Ruby scripts within browsers, d3.js and InfoVis, and these could be evaluated against their potential for bridging the gap between geospatial and non-spatial data.

We need a continuation of everything open – open data, open government, open source, etc. to ensure that decisions can be well-informed, resources allocated sustainably, and to ensure social equity.

We are moving away from just maps and if we are thinking about going deeper into Data Visualisation, we may need to learn some code just like some students are learning at schools across New Zealand, as in Figure 43.

Big data's greatest gift to us will be helping us to understand our environment, our people and our landscapes better and to make well-informed and empowered decisions.

Big data has been described as the single most important ingredient for creating 'Smart Cities' (Townsend, 2013). If this is true, and Smart Cities are a definite direction we need to focus on,

then we cannot afford to avoid the topic of fully understanding and analysing big data for site design.

Are there tools that landscape architecture can use to deal with big data? Yes. Do we make use of them? Not to any great extent, and one thing is clear: we cannot ignore the tsunami of data that is building. We need to find meaningful, enriching and relevant ways to collect it, understand it, analyse it, and design with it.

When it comes to landscape architecture and big data, it is crunch time.



FIGURE 43: What could the future of interfaces with big data be if coding is a basic literacy in education? Image: GeekGirl3.141 (2014)

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9.0 Appendix

UNECE big data classification types

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Big Data / Big Data in Official Statistics

Classification of Types of Big Data

Created and last modified by Steven Vale on 27 Jun, 2013

The following classification was developed by the Task Team on Big Data, in June 2013. Comments and feedback are welcome.

1. Social Networks (human-sourced information): this information is the record of human experiences, previously recorded in books and works of art, and later in photographs, audio and video. Human-sourced information is now almost entirely digitized and stored everywhere from personal computers to social networks. Data are loosely structured and often ungoverned.

1100. Social Networks: Facebook, Twitter, Tumblr etc.

1200. Blogs and comments

1300. Personal documents

1400. Pictures: Instagram, Flickr, Picasa etc.

1500. Videos: Youtube etc.

1600. Internet searches

1700. Mobile data content: text messages

1800. User-generated maps

1900. E-Mail

2. Traditional Business systems (process-mediated data): these processes record and monitor business events of interest, such as registering a customer, manufacturing a product, taking an order, etc. The process-mediated data thus collected is highly structured and includes transactions, reference tables and relationships, as well as the metadata that sets its context. Traditional business data is the vast majority of what IT managed and processed, in both operational and BI systems. Usually structured and stored in relational database systems. (Some sources belonging to this class may fall into the category of "Administrative data").

21. Data produced by Public Agencies

2110. Medical records

22. Data produced by businesses

2210. Commercial transactions

2220. Banking/stock records

2230. E-commerce

2240. Credit cards

3. Internet of Things (machine-generated data): derived from the phenomenal growth in the number of sensors and machines used to measure and record the events and situations in the physical world. The output of these sensors is machine-generated data, and from simple sensor records to complex computer logs, it is well structured. As sensors proliferate and data volumes grow, it is becoming an increasingly important component of the information stored and processed by many businesses. Its well-structured nature is suitable for computer processing, but its size and speed is beyond traditional approaches.

31. Data from sensors

311. Fixed sensors

3111. Home automation

3112. Weather/pollution sensors

3113. Traffic sensors/webcam

3114. Scientific sensors

3115. Security/surveillance videos/images

312. Mobile sensors (tracking)

3121. Mobile phone location

3122. Cars

3123. Satellite images

32. Data from computer systems

3210. Logs

3220. Web logs

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The new [beta.data.govt.nz](http://beta.data.govt.nz/?utm_source=live_link&utm_medium=dgn&utm_campaign=dgn_beta_0616) (http://beta.data.govt.nz/?utm_source=live_link&utm_medium=dgn&utm_campaign=dgn_beta_0616) site has been released - tell us what you think (https://www.govt.nz/browse/engaging-with-government/feedback-on-beta-data-govt-nz/?utm_source=live_feedback_link&utm_medium=dgn&utm_campaign=dgn_beta_0616).

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[Injury Statistics - Work-related claims \(CSV, Spreadsheet, HTML\)](#)
(<https://data.govt.nz/dataset/show/5709>)

[Sport NZ Group investments 2013 - 2014 \(CSV\)](#)
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[New Zealand Gazette \(XML, JSON\)](#)
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[Employment \(search/?CategoryID=6&q\)](#)

[Energy \(search/?CategoryID=7&q\)](#)

[Environment and conservation \(search/?CategoryID=8&q\)](#)

[View less](#)

Sample dataset: Vehicle count

[illegible]

WILLIS ST (1666)	WILLIS ST 227m SCATS 0350	08/02/2010	9129 MERCER ST	BOND ST	SCATS - (1 WAY) - 2 LANES, 2 DETECTORS, STH WST APP
WILLIS ST (1666)	WILLIS ST 11m SCATS 0320	08/02/2010	6143 WILLESTON ST	MERCER ST	SCATS - WILLIS ST - 2 LANES, 2 DETECTORS, STH WST APP
HUNTER ST (736)	HUNTER ST 82m SCATS 0310	08/02/2010	10233 LAMBERTON QUAY	CUSTOMHOUSE QUAY	SCATS (1 WAY) - 3 LANES, 2 DETECTORS, NTH WST APP
FEATHERSTON ST (522)	FEATHERSTON ST 867m SCATS 0290	08/02/2010	10413 GREY ST	HUNTER ST	SCATS - (1 WAY) - 2 LANES, 2 DETECTORS, NTH EST APP
FEATHERSTON ST (522)	FEATHERSTON ST 772m SCATS 0285	08/02/2010	9707 PANAMA ST	GREY ST	SCATS - (1 WAY) - 2 LANES, 2 DETECTORS, NTH EST APP
THE TERRACE (1510)	THE TERRACE 755m SCATS 0270	08/02/2010	7426 THE TERRACE SLIP	EVERTON TCE	SCATS - 2 LANES, 2 DETECTORS, NTH EST APP
JERVOIS QUAY-WEST (3257)	JERVOIS QUAY-WEST 705m SCATS 0240	08/02/2010	21712 HUNTER ST	POST OFFICE SQ	SCATS - 2 LANES, 2 DETECTORS, STH APP1 DET @ POLYTECH
DANIELL ST (411)	DANIELL ST 410m	09/02/2010	5241 NEWTOWN AVE	ROLLSTON ST	SCATS - 2 LANES, 2 DETECTORS, NTH APP1 DET @ POLYTECH
WALLACE ST (1615)	WALLACE ST 49m SCATS 0860	15/02/2010	19003 BIDWILL ST	BIDWILL ST	CUBA ST
WALLACE ST (1615)	WALLACE ST 23m SCATS 0860	15/02/2010	11646 HANKEY ST	DIXON ST	SCATS - 3 LANES, 3 DETECTORS, NTH EST APP
DIXON ST (435)	DIXON ST 189m SCATS 0440	15/02/2010	7043 EVA ST	HUNTER ST	SCATS - 3 LANES, 4 DETECTORS, STH APP2 DET @ EVENT CEN
VICTORIA ST (1590)	VICTORIA ST 823m SCATS 0430	15/02/2010	7852 MANNERS ST	HUNTER ST	SCATS - 3 DETECTORS, STH APP1 DET @ WHARF
JERVOIS QUAY-WEST (3257)	JERVOIS QUAY-WEST 599m SCATS 0315	15/02/2010	21928 WILLESTON ST	QUEENS DR-LYALL PDE RAB	
JERVOIS QUAY (788)	JERVOIS QUAY 216m SCATS 0315	15/02/2010	20457 QUEENS WHARF	BYRON ST	
MAJORIBANKS ST (832)	MAJORIBANKS ST 40m	20/02/2010	7226 KENT TCE	KINGSFORD SMTH ST	
WELLINGTON RD (1640)	WELLINGTON RD 95m	12/03/2010	9132 HENRY ST	LYALL PDE-TRANGI RD RAB	
LYALL PDE (912)	LYALL PDE 1167m	12/03/2010	7467 RUA ST	TANERA CRES	
PARK RD (1174)	PARK RD 178m	17/03/2010	6092 TAHI ST	KILBIRNIE CRES	
LYALL PDE (912)	LYALL PDE 389m	20/03/2010	6892 LYALL PDE-TRANGI RD RAB	CHILKA ST	
LYALL PDE (912)	LYALL PDE 271m	20/03/2010	6168 COCHRANE ST	MERSEY ST	
OHIRO RD (1122)	OHIRO RD 1011m	04/05/2010	13286 BROOKLYN RD	MANHARA ST	
EVANS BAY PDE (509)	EVANS BAY PDE 4110m	04/05/2010	5832 KEMP ST	NGAIO GORGE RD	
ADELAIDE RD (12)	ADELAIDE RD 1388m	08/05/2010	10887 COL OMBRO ST	WARPORI ST	
ADELAIDE RD (12)	ADELAIDE RD 2316m	08/05/2010	12446 BRITOMART ST	ASCOT ST	
THE PARADE (1505)	THE PARADE 970m	08/05/2010	7678 MIDWAY ST	ONSLow RD	
COUTTS ST (388)	COUTTS ST 230m	13/05/2010	5546 ONEPU RD	ONSLow RD	
KAIWHARAHARA RD (788)	KAIWHARAHARA RD 576m	26/06/2010	10979 OLD PORIRUA RD	AOEA QUAY-SOUTH-END ISL RHS	
ADELAIDE RD (12)	ADELAIDE RD 1720m	01/07/2010	9518 TORQUAY TCE	TAMAR ST	
TINAKORI RD (1518)	TINAKORI RD 1474m	17/07/2010	11795 UPTON TCE	TORY ST	
HUTT RD (3402)	HUTT RD 2040m	23/07/2010	17956 RANGIORA AVE	PITCHARD ST	
HUTT RD-SOUTH (3100)	HUTT RD-SOUTH 200m	20/07/2010	7731 JARDEN MILE	CABLE ST	
HUTT RD-CBD (3401)	HUTT RD-CBD 359m	23/07/2010	17849 SAR ST	FREDERICK ST	
HUTT RD (3402)	HUTT RD 1180m	23/07/2010	18788 KAIWHARAHARA RD	TARANAKI ST	
THE PARADE (1505)	THE PARADE 209m	23/07/2010	10510 DEE ST	JOHNSTON ST	
CABLE ST (246)	CABLE ST 30m	28/07/2010	17110 TARANAKI ST	SILVERBUSH GR	
STEWART DR (1423)	STEWART DR 196m	31/07/2010	5604 BATCHELOR ST	VICTORIA ST	
ORIENTAL PDE (1147)	ORIENTAL PDE 64m	03/08/2010	16332 KENT TCE	TORY ST	
WILLIS ST (1666)	WILLIS ST 122m	04/08/2010	11410 ARD ST	CABLE ST	
TARANAKI ST (1477)	TARANAKI ST 695m	11/08/2010	18912 VIVIAN ST	WEBB ST	
GHUZNEE ST (579)	GHUZNEE ST 610m	11/08/2010	12268 MARION ST	TARANAKI ST	
JERVOIS QUAY (788)	JERVOIS QUAY 262m	12/08/2010	17212 HUNTER ST	JOHNSTON ST	
LAMBERTON QUAY (857)	LAMBERTON QUAY 420m	12/08/2010	5384 BRANDON ST	SILVERBUSH GR	
MODERLON RD (1003)	MODERLON RD 727m	19/08/2010	7478 BURDENDALE GR	VICTORIA ST	
GHUZNEE ST (579)	GHUZNEE ST 267m	19/08/2010	13464 WILLIS ST	TORY ST	
WAKEFIELD ST (1611)	WAKEFIELD ST 225m	21/08/2010	15042 ALLEN ST	CABLE ST	
JERVOIS QUAY (788)	JERVOIS QUAY 570m	21/08/2010	17059 HARRIS ST	BOLTON ST	
THE TERRACE (1510)	THE TERRACE 60m	02/09/2010	8996 BOWEN ST	WAKANA ST	
MOOREFIELD RD (1039)	MOOREFIELD RD 246m	07/09/2010	13434 FRANKMOORE AVE	PETERBICK CRES	
HELSTON RD (878)	HELSTON RD 175m	07/09/2010	12228 EAST BRIDGE 2ND ABUT	CUSTOMHOUSE QUAY	
WHITMORE ST (1656)	WHITMORE ST 227m	08/09/2010	11428 FEATHERSTON ST	WATERLOO QUAY	
LAMBERTON QUAY (857)	LAMBERTON QUAY 544m	08/09/2010	5291 WARRING TAYLOR ST	END OF SH1 OFFRAMP	
AOEA QUAY (53)	AOEA QUAY 434m	13/09/2010	25207 WATERLOO QUAY	BOLD ST	
BRODERICK RD (204)	BRODERICK RD 183m	17/09/2010	9591 GOTHIC ST	HARRIS ST	
VICTORIA ST (1590)	VICTORIA ST 159m	19/09/2010	9702 WILLESTON ST	MANMERS ST	
TARANAKI ST (1477)	TARANAKI ST 244m	13/10/2010	14912 LUKES LANE	FINDLAY ST	
LINDEN AVE (2024)	LINDEN AVE 50m	14/10/2010	7108 MAIN RD	HINUAI ST	
COLLINS AVE (1984)	COLLINS AVE 118m	10/10/2010	1484 RAILWAY CROSSING	STELLA GR	
NEWLANDS RD (1083)	NEWLANDS RD 785m	09/11/2010	9614 BLACK ROCK RD	OVERBRIDGE 1ST ABUT	
WESTCHESTER DR EAST (1896)	WESTCHESTER DR EAST 328m	10/11/2010	5615 MIDDLETON RD	MCLELLAN ST	
MAIN RD (1973)	MAIN RD 2877m	10/11/2010	14941 VICTORY CRES	THOMAS HOOK ST	
MAIN RD (1973)	MAIN RD 3811m	10/11/2010	16781 LINDEN AVE	REMBRANDT AVE	
MAIN RD (1973)	MAIN RD 4182m	10/11/2010	12283 WALL PL	GLENSIDE RD	
MIDDLETON RD (1003)	MIDDLETON RD 1694m	16/11/2010	8171 HALSWATER DR	DIXON ST	
THE TERRACE (1510)	THE TERRACE 1272m	20/11/2010	16619 SALAMANKA RD	KOHIMA DR	
BURMA RD (231)	BURMA RD 1320m	12/12/2010	14648 KIM ST	LUCKNOW TCE	
KHANDALLAH RD (817)	KHANDALLAH RD 245m	08/02/2011	10776 COCKAYNE RD	TARANAKA ST	
KHANDALLAH RD (817)	KHANDALLAH RD 688m	08/02/2011	11655 NGATOTO ST	COCKAYNE RD-BOX HILL RAB	
COCKAYNE RD (353)	COCKAYNE RD 1740m	10/02/2011	11457 KHANDALLAH RD	LOHA ST	
ONSLow RD (1134)	ONSLow RD 1020m	10/02/2011	5638 HOMEBUSH RD	GRANT RD-SLIP	
GRANT RD (814)	GRANT RD 14m	10/02/2011	6999 GOLDIES BONE	RAUKAWA ST	
MONORGAN RD (1031)	MONORGAN RD 90m	18/02/2011	5119 BROADWAY	MONORGAN RD	
BROADWAY (201)	BROADWAY 652m	23/02/2011	12574 CRAWFORD GREEN	ATHENS ST	
PARA ST (1173)	PARA ST 50m	22/03/2011	6048 MIRAMAR AVE	REX ST	
PARA ST (1173)	PARA ST 450m	22/03/2011	5965 ASHLEIGH CRES	SEA TOUN TUNNEL	
BROADWAY (201)	BROADWAY 1500m	24/03/2011	5967 CAVENTISH SQ	IRA ST-BROADWAY RAB	
BROADWAY (201)	BROADWAY 526m	25/03/2011	11130 IRA ST-BROADWAY RAB	CHELSEA ST	
MIRAMAR AVE (1015)	MIRAMAR AVE 587m	25/03/2011	8792 PARK RD-HOBART ST RAB	STONE ST	
PARK RD (1174)	PARK RD 96m	25/03/2011	7906 PARK RD-SLIP	COCHRANE ST	
MIRAMAR AVE (1015)	MIRAMAR AVE 191m	05/04/2011	20013 MIRAMAR RD TAUHINU RD RAB	ALEXANDRA RD	
LYALL PDE (912)	LYALL PDE 87m	05/04/2011	5763 MOA POINT RD	FREYBERG ST	
CONSTABLE ST (371)	CONSTABLE ST 345m	05/05/2011	18044 COROMANDEL ST	BORLASE ST	
QUEENS DR (1237)	QUEENS DR 274m	03/05/2011	5283 ENDEAVOUR ST	BRIGHTON CEN	
OHIRO RD (1122)	OHIRO RD 1849	05/05/2011	6078 BUTT ST	DEE ST	
THE ESPLANADE (1504)	THE ESPLANADE 1086m	20/05/2011	5913 HOUGHTON BAY RD	HUMBER ST	
THE PARADE (1505)	THE PARADE 50m	20/05/2011	11352 DOVER ST	WHA ST	
THE PARADE (1505)	THE PARADE 1320m	20/05/2011	3801 MERSET ST	APU CRES	
ONEPU RD (709m)	ONEPU RD 709m	20/05/2011	6904 RESOLUTION ST	CHIRO RD	
ONEPU RD (1133)	ONEPU RD 963m	20/05/2011	5712 APU CRES	NAIRN ST	
HAPPY VALLEY RD (845)	HAPPY VALLEY RD 1607m	06/06/2011	5433 LANEFILL RD	HAPPY VALLEY RD	
BROOKLYN RD (208)	BROOKLYN RD 160m	09/06/2011	10884 WILLIS ST	CHILDERN ST	
OHIRO RD (1122)	OHIRO RD 2134m	09/06/2011	5843 BORLASE ST	BAY RD	
KILBIRNIE CRES (820)	KILBIRNIE CRES 466m	21/06/2011	9373 TULLY ST	ONEPU RD	
RONGOTAI RD (1309)	RONGOTAI RD 69m	21/06/2011	8388 CRAWFORD ST	CORHAM DR-TROY ST RAB	
RONGOTAI RD (1309)	RONGOTAI RD 180m	21/06/2011	8677 BAY RD	ONEPU RD	
TROY ST (1554)	TROY ST 136m	24/06/2011	7098 KEMP ST	ONEPU RD	
CRAWFORD RD (392)	CRAWFORD RD 740m	02/07/2011	12794 NAUGHTON TCE	ONEPU RD	
ADELAIDE RD (12)	ADELAIDE RD 2067m	07/07/2011	9720 WARPORI ST	ONEPU RD	
RINTOUL ST (1297)	RINTOUL ST 872m	06/07/2011	7674 WARPORI ST	ONEPU RD	
RIDOFORD ST (1640)	RIDOFORD ST 467m	07/07/2011	19102 MEN ST	ONEPU RD	
WELLINGTON RD (1640)	WELLINGTON RD 254m	07/07/2011	10296 CRAWFORD RD-WELLINGTON RD RAB	ONEPU RD	
BOWEN ST (184)	CAMBRIDGE TCE 326m	22/07/2011	8563 BALLANTRAE PL	ONEPU RD	
CAMBRIDGE TCE (261)	THE TERRACE 574m	22/07/2011	16907 COLLEGE ST	ONEPU RD	
WEBB ST (1634)	WEBB ST 343m	23/07/2011	8966 DALMULANE	ONEPU RD	
RIDOFORD ST (1294)	WEBB ST 694m	03/08/2011	7074 THOMPSON ST	ONEPU RD	
WEBB ST (1634)	WEBB ST 50m	08/08/2011	18869 WILSON ST	ONEPU RD	
ADELAIDE RD (12)	ADELAIDE RD 1200m	04/08/2011	7124 TARANAKI ST	ONEPU RD	
RIDOFORD ST (1294)	ADELAIDE RD 1559m	04/08/2011	11004 HALL ST	ONEPU RD	
ADELAIDE RD (12)	PARK RD 470m	04/08/2011	12358 CHILKA ST	ONEPU RD	
PARK RD (1174)	PARK RD 871m	04/08/2011	12903 NEWTOWN AVE	ONEPU RD	
GLENNMORE ST (595)	GLENNMORE ST 1656m	05/08/2011	10340 MUGGES LANE	ONEPU RD	
CHAYTOR ST (308)	CHAYTOR ST 80m	10/08/2011	6093 ROTHERHAM TCE	ONEPU RD	
TORY ST (1538)	TORY ST 820m	11/08/2011	16257 NORTHLAND RD	ONEPU RD	
IRA ST (752)	IRA ST 72m	13/08/2011	11749 BIRDWOOD ST	ONEPU RD	
MOLESWORTH ST (1025)	MOLESWORTH ST 141m	18/08/2011	6703 FRANCIS PL	ONEPU RD	
WAKEFIELD ST (1611)	WAKEFIELD ST 79m	24/08/2011	5903 THE QUADRANT	ONEPU RD	
ORIENTAL PDE (1147)	ORIENTAL PDE 165m	26/08/2011	7187 KATE SHEPPARD PL	ONEPU RD	
CABLE ST (246)	CHAFFERS ST 40m	26/08/2011	16105 CAMBRIDGE TCE	ONEPU RD	
CHAFFERS ST (259)	GHUZNEE ST 397m	26/08/2011	18982 CABLE ST	ONEPU RD	
GHUZNEE ST (579)	MURPHY ST 202	26/08/2011	19218 CHAFFERS ST	ONEPU RD	
MURPHY ST (1058)	THORNDON QUAY 1514	26/08/2011	6847 WAKEFIELD ST	ONEPU RD	
THORNDON QUAY (1514)	THORNDON QUAY 850m	31/08/2011	13790 VICTORIA ST	ONEPU RD	
ADELAIDE RD (12)	ADELAIDE RD 325m	01/09/2011	9395 SH 1 OFFRAMP	ONEPU RD	
JOHN ST (772)	JOHN ST 223m	01/09/2011	10546 MUGGRAVE ST	ONEPU RD	
KARORI RD (798)	KARORI RD 518m	01/09/2011	9430 DAVIS ST	ONEPU RD	
KARORI RD (798)	KARORI RD 871m	06/09/2011	20568 KING ST	ONEPU RD	
MOXHAM AVE (1052)	MOXHAM AVE 460m	06/09/2011	18818 TASMAN ST	ONEPU RD	
MOXHAM AVE (1052)	MOXHAM AVE 460m	22/09/2011	18102 LANCASTER ST	ONEPU RD	
TAURIMA ST (1484)	TAURIMA ST 220m	23/09/2011	16470 DONALD ST	ONEPU RD	
HAMILTON RD (640)	HAMILTON RD 826m	27/09/2011	5718 TAURIMA ST	ONEPU RD	
ORIENTAL PDE (1147)	ORIENTAL PDE 1174m	27/09/2011	5609 RAUPO ST	ONEPU RD	
DIXON ST (435)	DIXON ST 780m	27/09/2011	9227 RUAHINE ST	ONEPU RD	
DIXON ST (435)	VICTORIA ST 1073m	28/10/2011	5860 KUPE ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	28/10/2011	16187 ORIENTAL PDE-#186	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	28/10/2011	14130 GRASS ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	01/11/2011	6225 EGMONT ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	01/11/2011	6736 VICTORIA ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	01/11/2011	8942 VICTORIA ST-#175 SLIP	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	01/11/2011	12001 VIVIAN ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	02/11/2011	13516 LAMBERTON QUAY-EAST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	02/11/2011	9520 PIPTA ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	03/11/2011	12541 EAGLE ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	09/11/2011	8304 VIVIAN ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	09/11/2011	10525 VICTORIA ST-#195 SLIP	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	09/11/2011	10286 COURTNEYAY PL	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	24/11/2011	8203 WATCH ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	11/11/2011	19500 NOTTINGHAM ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	11/11/2011	7754 TRINGHAM ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	18/11/2011	14129 CUBA ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	18/11/2011	12443 RATA RD	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	19/11/2011	12206 BELVEDERE RD	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	23/11/2011	5974 CUBA ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	23/11/2011	14954 CAMPBELL ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	23/11/2011	15243 PARKVALE RD	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	30/11/2011	6853 WHITEHEAD RD	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	06/12/2011	9510 BOWEN ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	06/12/2011	12822 ALPHA ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	06/12/2011	12079 COURTNEYAY PL	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	06/12/2011	16609 BUNNY ST	ONEPU RD	
VICTORIA ST (1590)	VICTORIA ST 1073m	06/12/2011	5099 ALLEN ST	ONEPU RD	

CABLE ST (248)		09/12/2011	2048 JERVOIS QUAY-EAST	TARANAKI ST
CAMBRIDGE TCE (261)	CAMBRIDGE TCE 186m	09/12/2011	1173 BARKER ST	FIFESHIRE AVE
KENT TCE (813)		09/12/2011	2991 PIRE ST	ELLICE
COURTENAY PL (386)		09/12/2011	6940 TORY ST	TARANAKI ST
COURTENAY-PL-NORTH (3054)		09/12/2011	5508 TARANAKI ST	TORY ST
WATERLOO QUAY (1629)	WATERLOO QUAY 70m	13/12/2011	1078 WHITMORE ST	BUNNY ST
WATERLOO QUAY (1629)		08/02/2012	1498 BUNNY ST	HENKOA ST
WILLIS ST (1668)		09/02/2012	7201 DIXON ST	GHUZNEE ST
THE TERRACE 225m		09/02/2012	882 DOLTON ST	GHUZNEE ST
THE TERRACE (1510)	THE TERRACE 1402m	09/02/2012	4629 MCCONALD CRES	GHUZNEE ST
THE TERRACE (1510)	THE TERRACE 450m	09/02/2012	9643 SHEL LANE	GAUMUR LANE
WILLIS ST (1668)	WILLIS ST 432m	10/02/2012	10773 FLAGSTAFF LANE	DIXON ST
WILLIS ST (1668)		10/02/2012	7841 GHUZNEE ST	VIVIAN ST
WAKEFIELD ST (1611)	WAKEFIELD ST 158m	10/02/2012	1844 CHAFFERS ST	ALLEN ST
VICTORIA ST (1556)		15/02/2012	7589 HARRIS ST	MERCER ST
WAKEFIELD ST (1611)		15/02/2012	6786 CUBA ST	VICTORIA ST
KENT TCE (813)	KENT TCE 80m	15/02/2012	11227 WAKEFIELD ST	COURTENAY PL
JERVOIS QUAY-WEST (3257)		16/02/2012	17078 POST OFFICE SQ	BRANDON ST
RUAHINE ST (1329)	RUAHINE ST 200m	16/02/2012	31802 WELLINGTON RD	GOA ST
RUAHINE ST (1329)	RUAHINE ST 705m	16/02/2012	31148 GOA ST	TAURIMA ST
JERVOIS QUAY (768)		16/02/2012	16503 BRANDON ST	QUEENS WHARF
BRODERICK RD (204)		21/02/2012	6007 BANISTER AVE	CORTINA AVE
BRODERICK RD (204)		28/02/2012	9300 BOULST ST	MOOREFIELD RD
BRODERICK RD (204)		29/02/2012	6652 DR TAYLOR TCE	PHILLIP ST
STEWART DR (1423)		08/03/2012	8712 TED GILBERT PL	HELISTON ST
WAKEFIELD ST (1611)		13/03/2012	8828 TARANAKI ST	PRINGLE AVE
WAKEFIELD ST (1611)		13/03/2012	19377 TORY ST	TARANAKI ST
BOLCOTT ST (179)		13/03/2012	7630 WILLIS ST	CHURCH ST
MOOREFIELD RD (1039)		22/03/2012	12363 STEPHEN ST	HAUMA ST-MOOREFIELD RD RAB
MOOREFIELD RD (1039)		23/03/2012	1218 BRODERICK RD	STEPHEN ST
JERVOIS QUAY-WEST (3257)		28/03/2012	1810 HARRIS ST	WILLESTON ST
JERVOIS QUAY (768)	JERVOIS QUAY 430m	28/03/2012	1752 WILLESTON ST	HARRIS ST
JOHNSVILLE RD (774)		28/03/2012	10270 DSRAELI ST	BRODERICK RD
TORY ST (1536)	TORY ST 274m	29/03/2012	745 COURTENAY PL	FORRESTER LANE
CUSTOMHOUSE QUAY (407)		29/03/2012	1588 WHITMORE ST	WARING TAYLOR ST
HOKIOKI RD WEST (125)		04/04/2012	948 NEWLANDS RD-BRACKEN RD RAB	MCNEIRE ST
KHANDALLAH RD (817)		04/05/2012	1108 TARIKAKA ST	COLWAY ST
NEWLANDS RD (1083)		10/05/2012	9239 WESTLEIGH WAY	HOKIOKI RD WEST-BRACKEN RD RAB
STEWART DR (1423)		05/06/2012	566 BRACKEN RD	BATCHELOR ST
CASHMERE AVE (289)		11/05/2012	5763 RANUI CRES	RANUI CRES
BOX HILL (186)		11/05/2012	11119 CLARK ST	NICHOLSON RD-COCKAYNE RD RAB
STEWART DR (1423)		11/05/2012	6319 FITZPATRICK ST	WARWICK ST
WILTON RD (1689)		22/05/2012	5916 GLOUCESTER ST	KENYA ST
CROFTON RD (396)		23/05/2012	8572 OTTAWA-HAWKOWHAI ST RAB	TRELICKSC CRES
KENYA ST (815)		23/05/2012	8243 CROFTON RD	CHARTWELL DR
CHURCHILL RD (333)		08/06/2012	8741 SILVERSTREAM RD	SUROPHSHIRE AVE
WILTON RD (1689)		08/06/2012	5941 SURREY ST	BLACKBIDGE RD
CHURCHILL RD (333)		14/06/2012	8316 CHARTWELL DR	RANGORA AVE
HUTT RD (3402)	HUTT RD 1517m	21/06/2012	1034 PERITT ST	KAWIHARAWHARA RD
NCAD CORSE RD (1087)		22/06/2012	7544 ONSLOW RD	JARDEN MILE
HUTT RD (3402)		22/06/2012	6322 RARUA RD-RED LOOP	NORRA CRES
RARUA RD (1284)		22/06/2012	5164 CHAYTOR ST	NORTHLAND TUNNEL RD
RARUA CRES (1083)		22/06/2012	13670 THE TERRACE	MOUNT ST
SALAMANCA RD (1339)		08/12/2012	15770 BRODERICK RD	HAWAII ST
JOHNSVILLE RD (774)	JOHNSVILLE RD 318m	08/12/2012	11043 WANAKA ST	BRODERICK RD
MOOREFIELD RD (1039)	[049_001039_000455 2012-12-08] Moorefield I	01/03/2013	5218 IRONSIDE RD	ANGELL ST
BASSETT RD (124)	[049_001024_000078 2012-07-27] Bassett Rd	01/03/2013	7445 HILTON RD-BASSETT RD RAB	BRODERICK RD
MIDDLETON RD (1003)	[049_001003_000386 2012-03-02] Middleton F	02/03/2013	13455 MOOREFIELD RD-HAUMA ST RAB	JOHN SIMS DR
BURMA RD (231)	[049_000321_000378 2012-08-04] Burma Rd	02/03/2013	5087 JOHNSVILLE RD	POLLEN ST
FRASER AVE (580)	[049_000580_000233 2012-08-04] Fraser Ave	02/03/2013	5167 BLOOMSBURY GR	OTLANDS RD
HOKIOKI RD WEST (725)	[049_000725_000478 2013-03-02] Hokioki Rd	03/04/2013	14990 MOOREFIELD RD-JOHNNSVILLE RD RAB	FRANKMORRE AVE
MOOREFIELD RD (1039)	[049_001039_000685 2012-07-20] Newlands F	03/04/2013	14138 SHI DRIVE-SECTION SIGN	CLARKE RD
NEWLANDS RD (1083)	[049_001083_000460 2012-08-14] Stewart Dr	03/04/2013	5279 LOSABY CRES	QUIGLEY ST
STEWART DR (1423)	[049_001423_000098 2012-08-07] Broderick F	11/04/2013	9399 JOHNSVILLE RD	GOTHIC ST
BRODERICK RD (204)	[049_001204_000152 2013-05-09] Main Rd O	12/04/2013	1712 WILLOWBANK RD	MCNEIRE ST
MAIN RD (1573)	[049_001573_000176 2013-05-14] Main Rd O	16/04/2013	19411 CORLETT ST	DISRAELI ST
JOHNSVILLE RD (774)	[049_000774_000174 2013-04-16] Helston Rd	09/05/2013	9035 PETHERICK CRES	WILSON ST
HELISTON RD (879)	[049_000879_000277 2013-08-14] Helston Rd	09/05/2013	14362 CAMBRIDGE ST-MAIN RD RAB	WILSON ST
MAIN RD (1573)	[049_001573_000183 2013-05-09] Main Rd O	09/05/2013	14006 ELENA PL	CAMBRIDGE ST-MAIN RD RAB
MAIN RD (1573)	[049_001573_000183 2013-05-09] Main Rd O	09/05/2013	14006 ELENA PL	CAMBRIDGE ST-MAIN RD RAB
MOLESWORTH ST (1025)	[049_001025_000516 2013-05-22] Molesworth	22/05/2013	9480 HAWKESTONE ST	TEOFORD ST
BRODERICK RD (204)	[049_000204_000534 2012-08-07] Broderick I	07/06/2013	6866 PHILLIP ST	MAY ST
ONSLOW RD (1134)	[049_001134_000156 2013-06-11] Victoria St	11/06/2013	7560 HUNTER ST	BANISTER AVE
VICTORIA ST (1590)	[049_001590_000303 2013-06-11] Victoria St	11/06/2013	5738 MOORHOUSE ST	ANDANALY TCE
LINNEL RD (871)	[049_000871_000575 2013-06-19] Linnel Rd	19/06/2013	8941 PIPITIA ST	WILLETSON ST
MILGRAVE ST (1057)	[049_001057_000303 2013-06-19] Milgrave St	19/06/2013	7917 TINKARI RD	PIIT ST
PARK ST (1175)	[049_001175_000340 2013-06-19] Park St O	19/06/2013	7917 TINKARI RD	PIIT ST
WADSTOWN RD (1599)	[049_001599_001183 2013-06-19] Wadstow	19/06/2013	7917 TINKARI RD	BURNELL AVE
GLENNORE ST (95)	[049_000595_000688 2013-06-25] Glenmore F	25/06/2013	12287 ORANGI KAUPAPA RD	CCOL RD
OTTAWA RD (1154)	[049_001154_000175 2013-04-03] Ottawa Rd	25/06/2013	1334 AWARUA ST-OTTAWA RD RAB	CRIEFF ST
RARUA RD (1284)	[049_001284_000152 2013-06-28] Rarua Rd	26/06/2013	6123 CLUNAY AVE AVE	OTTAWA RD-CROFTON RD RAB
UPLAND RD (1571)	[049_001571_000775 2013-06-28] Upland Rd	26/06/2013	10778 ST MICHAELS CRES	BORON CRES
BOWEN ST (184)	[049_00184_000188 2013-07-03] Tinkari Rd	27/06/2013	876 SYDNEY ST WEST	PLUNKET ST
TINKARI RD (1518)	[049_001518_000430 2013-07-04] Murphy St	04/07/2013	10020 LITTLE PIPITIA ST	TINKARI RD
MURPHY ST (1058)	[049_001058_000430 2013-07-04] Murphy St	04/07/2013	10020 LITTLE PIPITIA ST	TINKARI RD
TINKARI RD 4th	[049_001518_000857 2013-07-04] Park St O	04/07/2013	1386 THORNBALL CRES	BOWEN ST
TINKARI RD (1518)	[049_001518_000857 2013-07-04] Park St O	04/07/2013	1386 THORNBALL CRES	BOWEN ST
BOLCOTT ST (179)	[049_000179_000568 2013-07-05] Bolcott St	05/07/2013	5338 OVERBRIDGE 2ND ABUT	PIPETIA ST
CLIFTON TCE (343)	[049_000343_000133 2013-07-05] Glagow St	05/07/2013	7625 SHI 1 CONRAVE	COTTLEWELL TCE
GLASGOW ST (588)	[049_000588_000808 2012-12-07] Blagow St	05/07/2013	10795 KELBURN PDE	WILSON TCE
MAIN RD (1573)	[049_001573_000275 2013-04-12] Main Rd O	30/07/2013	13680 ESSEX ST	RANGWIT TCE
CENTENNIAL HIGHWAY-WEST (214)	[049_002142_000075 2013-03-08] Centennial F	01/08/2013	13251 JARDEN MILE	LINCOLN AVE
CENTENNIAL HIGHWAY (9928)	[049_009928_000513 2013-02-08] Centennial F	31/07/2013	12381 WIDITH CHANGE-END BARRIER LHS	CENTENNIAL HIGHWAY ON RAMP
EVANS BAY PDE (509)	[049_000509_000391 2013-08-07] Evans Bay	07/08/2013	8888 WELLINGTON RD	JARDEN MILE
WALLACE ST (1515)	[049_001515_000590 2013-03-08] Wallace St	15/08/2013	19555 HOWARD ST	KEMP ST
BOLCOTT ST (179)	[049_000179_000440 2013-06-19] Park St O	19/06/2013	19555 HOWARD ST	KEMP ST
JOHNSVILLE RD (774)	[049_000774_000530 2013-04-11] The Terrace	17/08/2013	7628 AURORA ST	HUTCHINSON RD
THE TERRACE (1510)	[049_001510_000315 2013-08-17] The Terrace	17/08/2013	7628 AURORA ST	HUTCHINSON RD
THE TERRACE (1510)	[049_001510_000315 2013-08-17] The Terrace	17/08/2013	7628 AURORA ST	HUTCHINSON RD
DELAIDE RD (12)	[049_001510_000315 2013-08-17] The Terrace	22/08/2013	11808 EVERTON TCE	MOOREFIELD RD-JOHNNSVILLE RD RAB
JERVOIS QUAY-WEST (3257)	[049_003257_000080 2013-08-08] Jervois Quay	19/11/2013	17596 TARANAKI ST	SHELL LANE
CUSTOMHOUSE QUAY-WEST (3300)	[049_003300_000110 2013-08-28] Customhouse Quay	19/11/2013	21588 JOHNSVILLE RD	SALAMANCA RD
CUSTOMHOUSE QUAY-WEST (3300)	[049_003300_000110 2013-08-28] Customhouse Quay	19/11/2013	21588 JOHNSVILLE RD	SALAMANCA RD
KENT TCE (813)	[049_000813_000427 2014-02-20] Kent Tce C	20/02/2014	11031 ELIZABETH ST	ALLEN ST
CAMBRIDGE TCE (261)	[049_000261_000079 2014-02-20] Cambridge Tce	20/02/2014	11031 ELIZABETH ST	ALLEN ST
MIDDLETON RD (1003)	[049_001003_000814 2013-10-18] Middleton F	21/02/2014	6892 SILVERBIRCH GR	ALLEN ST
KAWIHARAWHARA RD (788)	[049_000788_000126 2013-07-30] Kawharau	25/02/2014	6520 PICKERING ST	ALLEN ST
BOWEN ST (184)	[049_000184_000117 2013-08-23] Bowen St	11/03/2014	6420 LAMBERT QUAY	ALLEN ST
HUTT RD-CBD (2401)	[049_002401_000951 2013-03-12] Adelaide Rd	07/03/2014	13168 AOTEA QUAY-END ISL LHS	ALLEN ST
HAPPY VALLEY RD (454)	[049_000454_001299 2013-10-31] Happy Valley	07/03/2014	5832 MURCHISON ST	ALLEN ST
CHAYTOR ST (308)	[049_000308_000070 2013-08-07] Crawford Rd	14/03/2014	18117 ALEXANDRA RD	ALLEN ST
CRAWFORD RD (392)	[049_000392_000070 2013-08-07] Crawford Rd	14/03/2014	18117 ALEXANDRA RD	ALLEN ST
KELBURN PDE (805)	[049_000805_000050 2013-03-21] Kelburn Pde	19/03/2014	14758 SALAMANCA RD	ALLEN ST
BROKLYN RD (208)	[049_000208_000605 2013-03-09] Broklyn Rd	19/03/2014	6197 NARIN ST	ALLEN ST
WATERLOO QUAY (1629)	[049_001629_000079 2013-03-13] Waterloo Quay	20/03/2014	4971 HENKOA ST	ALLEN ST
MOLESWORTH ST (1025)	[049_001025_000404 2013-03-20] Molesworth	21/03/2014	7301 LAMBERT QUAY	ALLEN ST
BOWEN ST (184)	[049_000184_000228 2013-03-12] Bowen St	21/03/2014	9386 THE TERRACE	ALLEN ST
GLENNORE ST (95)	[049_000595_000377 2013-10-31] Glenmore F	25/03/2014	15440 PATANGA CRES	ALLEN ST
CURTIS ST (408)	[049_000408_000807 2013-06-25] Curtis St O	25/03/2014	6855 LAMBERT RD	ALLEN ST
RARUA RD (1284)	[049_001284_000362 2013-10-18] Rarua Rd I	28/03/2014	6522 ENTRANCE ST	ALLEN ST
GRANT RD (814)	[049_000814_000374 2013-06-17] Grant Rd C	27/03/2014	7062 GRANT RD-SLIP	ALLEN ST
ARO ST (77)	[049_000777_000374 2013-06-17] Grant Rd C	27/03/2014	7062 GRANT RD-SLIP	ALLEN ST
EVANS BAY PDE (509)	[049_000509_000245 2013-09-20] Evans Bay	02/04/2014	9558 MAIDA VALANCE RD	ALLEN ST
BROADWAY (201)	[049_000201_000149 2013-11-08] Broadway F	09/04/2014	7671 BENTINCK AVE	ALLEN ST
CRAWFORD RD (392)	[049_000392_000556 2013-11-08] Crawford Rd	21/05/2014	12889 DUNCAN TCE	ALLEN ST
TINKARI RD (1518)	[049_001518_001648 2013-07-03] Tinkari Rd	21/05/2014	14981 BOWEN ST	ALLEN ST
THE PARADE (1525)	[049_001525_000625 2013-06-25] The Parade	05/06/2014	9855 AVON ST	ALLEN ST
LUXFORD ST (168)	[049_000168_000146 2013-06-25] Wairangi St	18/06/2014	7488 RINTOUL ST	ALLEN ST
WAIKAWA ST (1621)	[049_001621_000146 2013-06-25] Wairangi St	18/06/2014	7488 RINTOUL ST	ALLEN ST
QUEENS DR (1237)	[049_001237_001447 2014-07-24] Queens Dr	24/07/2014	7200 LYALL PDE-QUEENS DR RAB	ALLEN ST
ARO ST (77)	[049_000777_000374 2013-06-17] Grant Rd C	27/03/2014	7062 GRANT RD-SLIP	ALLEN ST
MEIN ST (993)	[049_000993_000070 2014-08-13] Mein St	08/08/2014	9996 ALAMEDA TCE	ALLEN ST
RUSSELL TCE (1334)	[049_001334_000162 2014-08-15] Russell Tce	15/08/2014	10584 RIDGIFORD ST-MANSFIELD ST RAB	ALLEN ST
RIDGIFORD ST (1294)	[049_001294_000114 2014-08-22] Ridgifford S	22/08/2014	11977 GORDON ST	ALLEN ST
RIDGIFORD ST (1294)	[049_001294_000188 2014-08-22] Ridgifford S	22/08/2014	10988 ADELAIDE RD	ALLEN ST
RIDGIFORD ST (1294)	[049_001294_000188 2014-08-22] Ridgifford S	22/08/2014	10988 ADELAIDE RD	ALLEN ST
WILTON RD (1689)	[049_001689_000022 2012-08-24] Main Rd St	29/08/2014	16485 GREEN ST	ALLEN ST
WAKOWHAI ST (1603)	[049_001603_000379 2014-08-07] Wakowhahi	09/09/2014	15487 GEE ST	ALLEN ST
ONSLOW RD (1134)	[049_001134_000743 2014-08-08] Onslow Rd	09/09/2014	6040 ALBEMARLE RD	ALLEN ST
CHURCHILL RD (333)	[049_000333_001591 2012-09-07] Churchill D	09/09/2014	6343 OTTAWA RD-CROFTON RD RAB	ALLEN ST
BURMA RD (231)	[049_000231_000146 2013-08-07] Burma Rd	09/09/2014	5679 WILTON BUSH RD	ALLEN ST
BOX HILL (186)	[049_000186_000146 2013-08-07] Box Hill D	09/09/2014	12561 FRASER AVE	ALLEN ST
NEWLANDS RD (1083)	[049_001083_000379 2013-09-20] Newlands F	10/09/2014	13323 HURRING PL	ALLEN ST
MOLESWORTH ST (1025)	[049_001025_000248 2012-09-08] Molesworth	10/09/2014	8084 HILL ST	ALLEN ST
HELISTON RD (879)	[049_000879_000169 2014-08-11] Helston Rd	11/09/2014	6830 BROCKLETON RD-BASSETT RD RAB	ALLEN ST
ONEPU RD (1133)	[049_001133_000169 2014-08-11] Onepu Rd	11/09/2014	7795 RONGOTAI RD	ALLEN ST
RONGOTAI RD-SOUTH (9940)	[049_000994_000169 2014-08-11] Onepu Rd	11/09/2014	7795 RONGOTAI RD	ALLEN ST
RONGOTAI RD (1389)	[049_001389_000634 2014-09-16] Rongotai S	16/09/2014		

GROSVENOR TCE (821)	[049_000621_000201 2013-10-17] Grosvenor	11/10/2014	6406 GRANT RD	LOWER WATT ST	Vehicles = 76871 / 76891 (99.97%)
EVANS BAY PDE (509)	[049_000509_000300 2013-10-17] Evans Bay	11/10/2014	10346 ORIENTAL PDE	MAIDA VALE RD	Vehicles = 134492 / 134648 (99.88%)
BROADWAY (201)	BROADWAY 63m	11/10/2014	13015 CALABAR RD-BROADWAY RAB	KAURI ST	Vehicles = 169189 / 169295 (99.94%)
ADELAIDE RD (12)	[049_000012_002920 2013-03-12] Adelaide R	11/10/2014	11650 DURPA ST	DOVER ST	Vehicles = 139805 / 139895 (99.98%)
EVANS BAY PDE-SOUTH (3078)	[047_003078_000020 2014-10-14] Evans Bay	14/10/2014	5193 RONGOTAI RD	BAY RD	Vehicles = 51934 / 52010 (99.85%)
KARORI TUNNEL (9984)	[049_009984_000098 2013-12-05] Karori Tun	15/10/2014	16051 GLENMORE ST	WAIAPU RD	Vehicles = 144480 / 144620 (99.89%)
MIRAMU AVE (1015)	[049_001015_000040 2013-10-16] Miramar A	15/10/2014	10918 SHELLY BAY RD	MAUPUUA RD	Vehicles = 85591 / 85592 (99.97%)
BURMA RD (231)	BURMA RD 870m	05/11/2014	12230 JOHN SIMS DR	FRASER AVE	Vehicles = 85609 / 85691 (99.90%)
TIRANGI RD (1520)	[047_001520_000583 2014-11-11] Tirangi Rd	11/11/2014	9197 COUTTS ST	KINGSFORD SMITH ST	Vehicles = 64379 / 64418 (99.94%)
BROOKLYN RD (208)	BROOKLYN RD 1228m	18/11/2014	7630 WASHINGTON AVE	OHIO RD	Vehicles = 76295 / 76362 (99.91%)
COUTTS ST (888)	[047_000388_000878 2014-11-19] Coutts St C	19/11/2014	9767 MAMARI ST	TIRANGI RD	Vehicles = 68367 / 68415 (99.93%)
ADELAIDE RD (12)	[049_000012_000833 2013-03-31] Adelaide R	21/11/2014	11326 HOSPITAL RD	JOHN ST	Vehicles = 63483 / 63568 (99.90%)
ADELAIDE RD (12)	[049_000012_002196 2014-06-19] Adelaide R	21/11/2014	14681 LUXFORD ST	BRITOMART ST	Vehicles = 104870 / 104986 (99.89%)
OHIO RD (1122)	[049_001122_001277 2014-05-07] Ohio Rd C	29/11/2014	9093 TODMAN ST	MCKINLEY CRES	Vehicles = 63651 / 63736 (99.87%)
ADELAIDE RD (12)	[047_000012_000804 2014-12-12] Adelaide R	12/12/2014	10594 JOHN ST	NIKAU ST	Vehicles = 74157 / 74286 (99.85%)
CONSTABLE ST (371)	[047_000371_000189 2014-12-12] Constable S	12/12/2014	12001 RIDDIFORD ST	DANIELL ST	Vehicles = 84010 / 84118 (99.87%)
OHIO RD (1122)	CONSTABLE ST 367m	12/12/2014	15271 DANIELL ST	OWEN ST	Vehicles = 106994 / 107000 (99.90%)
LYALL PDE (912)	[048_001122_001091 2014-05-07] Ohio Rd C	12/12/2014	11821 TANERA CRES	TODMAN ST	Vehicles = 82745 / 82845 (99.88%)
LYALL PDE (912)	[047_000912_000795 2014-07-22] Lyall Pde C	19/02/2015	7658 KINGSFORD SMITH ST	ONEPU RD-LYALL PDE RAB	Vehicles = 53607 / 53667 (99.89%)
ONEPU RD (1133)	[047_000912_000912 2014-07-22] Lyall Pde C	19/02/2015	8552 ONEPU RD-LYALL PDE RAB	RUA ST	Vehicles = 66803 / 66833 (99.90%)
	[047_001133_001141 2014-07-22] Onepu Rd	19/02/2015	6485 APU CRES	LYALL PDE-ONEPU RD RAB	Vehicles = 45396 / 45449 (99.88%)

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Landscape Architecture and Big Data: It's Crunch Time

[illegible]

THIS DISSERTATION...

14,687
WORDS

491 hrs
29,489 min
EDITING TIME

73
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1,400 cups of coffee required

“data”
352 times

1:341
Graphic to word ratio

“data analysis”
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